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Real estate performance measurement in markets with thin information

A thesis presented by
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to

The Faculty of Finance in partial fulfilment of the requirements
for the degree of Doctor of Philosophy in the subject of Finance

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In memory of Luigi Giussani
who has opened my reason
to the category of the possible

ABSTRACT

Historically, different index construction methodologies have been used to represent the behaviour of real estate markets. They can be grouped into four main categories: valuation-based indexes and transaction-based ones, synthetic measures (e.g. created by using prime rents and yields) and vehicle-based performances (property companies and Real Estate Investment Trusts). Each measure requires a different set of data.

When we consider markets with thin information, data availability plays a major role in defining the applicability of these construction methodologies. Moreover, if the aim of an index is to show long-term performances in such markets, individual property data (e.g. periodic valuations) used by main index providers may not be retrievable historically.

This work describes main index construction methodologies used in the property industry or suggested in relevant finance literature. Three new methodologies are applied to the UK market and their ability to represent a “true” estimate of market performance is tested by comparing these new figures with the current valuation-based index. The first methodology employs purchase prices and last valuations to create repeated-measures regression returns. We find this index to behave more similarly to an unsmoothed version of the valuation-based index than to its original series. Secondly, we obtain an estimate of market performance from vehicle-based information by adopting a weighted average cost of capital framework. Finally, we apply a capital asset pricing model net of illiquidity costs to public real estate returns and find an improvement in correlation coefficients even at a monthly frequency.

All these three methodologies may be used to create historical series in markets where information are not easily available. They all represent a good proxy for unsmoothed real estate returns. The choice between these three methodologies should be data driven since there is no theoretical a-priori to prefer one to another.

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Chapter 1

INTRODUCTION AND STATEMENT OF OBJECTIVES

1.1 A LACK OF TRANSACTION FLOWS

The general belief that property performance measures are subjective and equity returns are objective is doubtful. As a matter of fact, problems arise from index construction methodologies in both markets. However, some issues are peculiar to the real estate market. First of all, properties are not transacted frequently. According to Investment Property Databank (IPD) – the largest provider of real estate indices worldwide – in the UK a commercial property is exchanged every nine years on average¹. The transaction price of a building is therefore not available at each measurement time (for example every year), and the lack of a continuous flow of transaction-based data limits the applicability of standard equity price indices to real estate markets.

In line with the previous finance literature, a recent Investment Property Forum Research Report [April 2004]² studies the liquidity issue in property markets and defines it as “a multi-dimensional concept”, which includes the trading volume and frequency, together with:

- Direct and indirect costs of trading;
- Risk and uncertainty concerning the timing of the sale;
- Risk and uncertainty concerning the achieved sale price;
- Time taken to execute a trade; and
- Price impact of the act of sale and purchase.

¹ The IPD database is biased towards institutional ownership.

² “Liquidity in Commercial Property Markets” (2004), by Bond et al.

Bond et al. [2004] use data from the Inland Revenue, Office for National Statistics, Investment Property Databank (IPD), Auction Results Analysis Service (ARAS) and Property Data to analyse trading activities in the UK direct property market. They find significant differences between commercial and residential markets. The Inland Revenue database shows an average turnover of around 5% (i.e. average holding period twenty years) in commercial markets, which increases to 12-15% for institutional investors, suggesting a median holding period of around six to seven years. Moreover they find that commercial property trades more frequently in the UK than in other European countries, with a turnover rate that was double the one found in France and the Netherlands in 2002.

This lack of transaction flows is due to several reasons. Real estate players are normally long-term investors and they aim to achieve a return over a period of several years. Hence, a property is normally bought because it guarantees a minimum income return from letting (net of operating costs) and a foreseeable capital growth. However, in order to realise this capital appreciation, the investor faces very high transaction costs which discourage a highly frequent trading activity. According to Marcato and Key [2005] for example, in the UK both purchases and sales normally cost 1.5% of value in professional fees (i.e. brokers, surveyors and lawyers). Larger investors, especially on large deals, would usually expect to see a reduction on these fees, but a 3% 'round trip' cost on buying and selling could be assumed as a reasonable average estimate. Transactions tax payable by buyers (and known as Stamp Duty in the UK) has since March 2000 been 4% of the value for transactions over £600,000. The current rate is

double the rate applied before 1998 and it thus represents a significant barrier to frequent trading. Finally, recognising that trading is highly management intensive, a further 0.5% internal cost could be added to the round trip costs of selling out of one property and buying into another. With these assumptions, a total cost of around 7.5% is reached, signalling a strong deterrent to short-term exit strategies.

Furthermore, buildings are heterogeneous (i.e. each property is unique) and it is not possible to hold, buy or sell a fraction of a building – while it is possible for a company by dividing its capital into shares. Due to the size of transactions, then, properties will be exchanged with a smaller frequency than other financial assets. Bond et al [2004] find that buying and selling activities vary by lot size, with many of the variations showing the expected direction: a high-value property trades less frequently than small lot sizes (standard shops, smaller offices) which instead tend to be more liquid.

Finally, the time to buy or to sell an asset is significantly higher for properties than for financial securities, such as bonds or equities. On average, the time from formal marketing to completion is found to be equal to ten months, this figure being slightly misleading since the distribution of sales is heavily skewed to the right. Bond et al. [2004] argue that it is preferable to refer to the median time to sale which is six months. They find that the longest period elapses between initiation to heads of terms (88 days), followed by due diligence (62 days) and the period between exchange and completion (19 days).

1.2 PERFORMANCE MEASUREMENT: VALUES VS. PRICES

The lack of information on transaction prices has induced the real estate industry to adopt valuation-based indices as the best estimate of market performances.

Since the same asset is not traded with a high frequency and there is not a sufficient flow of periodic transaction prices, valuation-based indices use individual property information on the periodic value assessed by an independent valuer as a proxy for the true estimate of its market price. This assumption is supported both theoretically and empirically. On one hand, valuers act according to the conceptual framework of the International Valuation Standards Committee and main property valuation guidelines – e.g. Red Book by the Royal Institute of Charter Surveyors (RICS) and European Valuation Standards by The European Group of Valuers' Associations (TEGoVA) – which define “market value” as:

“the estimated amount for which a property should exchange on the date of valuation between a willing buyer and a willing seller in an arm’s-length transaction after proper marketing wherein the parties had each acted knowledgeably, prudently and without compulsion.”³

³ Source: RICS Appraisal and Valuation Standards, Part 1, Chapter 3, PS3.2.

On the other hand, several studies have shown that, at least in stable markets, valuations are an accurate representation of transaction prices (refer to section 2.2.1 on valuation accuracy).

However, the impact of this issue on performance measurement has not been fully analysed yet and this debate is still alive and touches several important issues. Valuation is “by nature” subjective because it depends on both the valuer’s perception of the market cycle and his/her valuation method. In principle, the valuation method itself should not influence the outcome. However, the opposite may happen when the application of one of the methods requires a set of information that is not available. Consequently, if valuers use methods for which information is scarce, results may differ significantly.

1.3 THE INTER-TEMPORAL LINKAGE OF MARKET VALUES

Appraisers tend to adopt a conservative approach and they show new information with a temporal lag. The effects of this issue are visible more in thinly traded markets than in developed ones because there are fewer, recent comparables. In this context, in fact, in order to use a reasonable number of comparables, a valuer may need to go further back

into the past. These comparables will inevitably contain older information that will be shown by the new value even if it is not up-to-date.

In the real estate literature this issue is known as *temporal aggregation* and it represents one of the three reasons causing an inter-temporal linkage between market values. Geltner [1997] states that *“in the real temporal world, a finite number of comps [i.e. comparables] will be optimal as the appraiser must balance the advantage of a larger number of comps with the disadvantage of drawing comps from farther in the past”*.

The existence of an optimal number of comps is due to the trade-off between a pure random error – due to a small sample size for comparables – and a systematic bias – linked to a bigger sample size made up of observations containing old information. Moreover, he continues, suggesting that *“when the appraisal of an individual property is to be used in the construction of an aggregate value, only the most recent comparable should be used”* because purely random errors tend to cancel each other out and only the systematic component of the error remains at a portfolio level. However, appraisers do not value for the purpose of constructing an index, but to obtain the “best” market value for an individual property. They thus determine an inter-temporal linkage between values at the index level because they do not only use the most recent comparable.

The problem of temporal aggregation is even more significant when returns are measured with a higher frequency. If properties are appraised once a month, for example, the valuer is very likely to use comparables referring to deals completed during previous months – because during the month of the valuation there could have been too few (or no) comparable deals. Moreover, transaction data normally refer to the

completion date. If the time passing between heads of terms and the completion of the transaction is significant – i.e. 81 days (62+19) in Bond et al [2004] – monthly values will incorporate old information, thus inducing temporal aggregation. This would happen even if there are enough comparable sales during the month of the appraisal because comparables should be backdated on average by 81 days, i.e. almost three months.

A second main reason of inter-temporal linkage between market values is the existence of an anchoring point – i.e. the previous valuation figure – within the appraisal process. At least in more mature markets where appraisals are undertaken periodically, the previous figure is often easily available and each capital value thus tends to be “linked” to the previous one. This issue – known as “*anchoring effect*” – becomes more relevant for higher frequencies and it may be associated to two main driving factors.

Firstly, there is an *agency problem*. Valuers do not tend to change their valuations from one period to the next very often and they prefer to avoid continuous adjustments to market values. These corrections, in fact, would introduce a higher volatility of property returns, which may induce their clients to sell the property. The immediate consequence would thus be a business loss because periodic valuations will not be needed any longer.

Secondly, changes in values may be hidden and not reported by the valuer unless they are above a minimum threshold. Capital values will thus incorporate the cumulative small changes recorded during few periods (i.e. ‘*valuation inertia*’), rather than each independent periodic change. An example may clarify this point. Let us assume the

appraiser obtains an increment in the market value of a property, which is equal to 0.5%, 0.4% and 0.3% for three successive periods. If he/she fixes a minimum threshold of $\pm 1\%$ to report a change in the market value, he/she will not change the appraised figure until the third period, when he/she will state a cumulative 1.2% (c.ca) increase – i.e. sum of the previous three period changes – after no change in periods 1 and 2. The situation is even worse when positive and negative returns alternate. Let us now assume that the minimum threshold is kept at 1% and the value of the same property changes by 0.5%, -0.4% and 0.3% in three successive periods. The valuer will thus report no change in any of the three years (i.e. the threshold is never reached), even if a positive, followed by a negative, followed by a positive return should have been reported.

Finally, the impact of valuation inertia is magnified when the minimum threshold is established for underlying assumptions and not only for the final market value. Let us assume an appraiser uses an income approach. He/she may decide to fix a threshold for yield movements equal to $\pm 0.125\%$ (one eighth of a percentage point). If the yield is estimated to increase by 0.1%, the market value would decrease by $1.64\%^4$, but no change would be reported, simply because the yield shift has not reached the threshold.

At the index level, the valuation inertia problem is very similar to another issue that is identified mostly in US data and known as '*stale appraisal*'. Some properties are not actually revalued every period (e.g. quarter), but only over a longer time horizon (e.g.

⁴ If we assume a hypothetical market rent of 100, the market values at the beginning and at the end of the period will be respectively equal to: $CV_t = \frac{100}{0.06} = 1,666.67$ and $CV_{t+1} = \frac{100}{0.061} = 1,639.34$. Therefore, the decrease in value will be equal to: $\Delta Value = \frac{1,666.67 - 1,639.34}{1,666.67} = -1.64\%$.

every four quarters). In order to construct an index with higher frequency, however, the values of properties without an ‘actual appraisal’ are kept constant and these properties will thus show no change in capital values. This issue has the same effect of valuation inertia for monthly or quarterly frequencies: changes in individual property values show a sequence of zeros interrupted by either positive or negative numbers (when the property is actually appraised or the change of its value is above a minimum threshold). However, the nature of the two issues is different because valuation inertia happens even if the property is actually valued at each measurement time.

1.4 INVESTIBILITY, REPRESENTATIVITY, DIVERSIFICATION AND ASSET TYPES

In principle an index should be investible⁵. This means that each investor should be able to replicate it. However, in property markets there is no possibility of constructing a portfolio perfectly mimicking index performances because real estate assets – unlike equities or bonds – represent heterogeneous and indivisible investments. On the other hand, equities are not exempt from this issue because they face the problem of controlling shareholders and closely held shares. However, a solution in the equity market has been achieved by using a free-float rather than a capitalization-weighting.

⁵ See FTSE “Ground rules for the management of the UK series of the FTSE actuaries share indices” [2003].

In addition, an index should be representative of the overall market⁶. The sample should contain enough information to reflect the true market performance (i.e. the greater the sample, the lower the deviation of the index from true market figures). This rule is generally valid for all kinds of indices and creates problems for all financial assets (e.g. the Dow Jones Industrial Average index is not fairly representative of the US equity market). However, the sample dimension constitutes a bigger issue for real estate than for equities or bonds because the cost of collecting data is higher, properties are heterogeneous (each one is unique and affected by legal and physical factors) and they still convey a specific risk although the portfolio is well diversified (this risk is not reflected into equity or bond indices). For these reasons, even if it is acknowledged that a well-constructed sample may be better than a biased more comprehensive coverage, in the case of real estate markets we tend to prefer a high market coverage. In order to include the highest proportion of the market, Investment Property Databank collects information about as many properties as possible rather than working on a sampling basis (e.g. 45% of market coverage is reached in the UK). Instead, the National Council of Real Estate Investment Fiduciaries (i.e. NCREIF), not-for-profit organization providing US private real estate data, only covers less than 5% of the overall US market. The choice of market coverage may also affect the existing trade-off between index frequency and cost of data collection and elaboration. For equities, in fact, the

⁶ See FTSE "Ground rules for the management of the UK series of the FTSE actuaries share indices" [2003].

data collection process is cheaper and less time consuming than for properties, thus facilitating the construction of an index with a higher frequency.

Furthermore, different sectorial and/or regional distributions of properties included in the sample can affect performances: the index should therefore try to reflect the actual composition of the market. On one hand, if a sector performs very well and is underweighted in the sample, the index would show a return below the “true market return”. On the other hand, the regional allocation is also significant because properties belonging to the same sector but located in different regions may perform differently. Moreover, the definition of regional clusters has to be determined on the basis of their ability to explain property performances. In the UK Investment Property Databank decided to adopt a division based on standard Government Office Regions (i.e. GORs), but some studies⁷ suggested that other forms of regionalisation (e.g. economic districts) may be more powerful in explaining property performances than traditional GORs.

The last main issue associated with the composition of real estate indices is the choice of the type of assets to be included. Either actual or hypothetical properties may be used to create indices. The first type of buildings is actually held by investors (either as an investment or a development). A notional property, instead, does not exist in reality and is assumed to be “continuously new”. A notional rent (i.e. Open Market Rental Value) and market yields are then applied to value it – refer to section 2.3 for further information. The sample created with the first type of buildings is used to measure the actual performance current investors achieved. Indices using notional properties intend

⁷ E.g. Lee [2001].

to show an up-to-date measure of returns that an investor may obtain from short-term market movements. Moreover, as information is not easily available for all properties in the market place, real estate indices usually include specific types of assets (i.e. the prime sector, which includes the best slice of properties, offering the highest long-term performance). Finally, transactions and developments may or may not be included in the index. If only standing investments are used, the sample (number of properties composing the index) at the beginning of the period is as big as the one at the end of period. If the index includes transactions, a problem of how to consider a holding period shorter than the measurement interval arises (i.e. the property is bought/sold in the middle of the measurement period and shows figures referring only to a section of the entire period).

1.5 MARKETS WITH THIN INFORMATION

So far, we have analysed the main issues in performance measurement in real estate markets where comprehensive information is normally available. However, standard index construction methods require an amount of information which is not necessarily available in newly established markets, or those suffering a lower degree of transparency (e.g. Italy, Spain, Portugal, Greece).

In these markets a small number of investors normally holds a high proportion of the overall amount of available data. These investors tend to be reluctant to release

“unique” information which could be seen as a competitive advantage towards competitors. Two ways of handling this issue guarantee confidentiality to investors. The UK market developed a private entity (i.e. IPD) acting as an independent research company which avoids any possible conflict of interest arising with the handling of sensitive information (e.g. the company does not offer any advising-related activity or valuation service). In the US, instead, the market has opted for a not-for-profit organization (NCREIF), sponsored by investors.

Furthermore, standard valuation-based indices require detailed information for each individual property. In markets with thin information there are several situations in which, even if a reasonable number of investors is willing to provide information, a full set of data is not available (e.g. periodic valuations or cash flow data are not properly recorded or may be missing from period to period).

All these issues become even more problematic when we are concerned about historical series and the index is constructed retrospectively to represent past market cycles. In this context, the lack of data (or the existence of few specific data only) becomes a key input in the choice of the index construction methodology. For example, if we want to apply the IPD (or NCREIF) methodology, we need to obtain a record of past periodic valuations. This type of information, however, is not normally available in newly established markets and an alternative method not using this type of information has to be adopted.

However this is not only a major issue in newly established markets, but also in most developed markets (e.g. the UK and USA) which show a differential of information

levels between property and other asset classes (such as equities or bonds). In the UK and US, for example, historical series only go back to the 1970s, (in the UK there is an historical series going back to the late 1940s, but the index is constructed with a very thin sample⁸).

1.6 MAIN OBJECTIVES AND STRUCTURE

This thesis has the main objective of identifying three different methodologies to construct historical real estate indices in markets where very little information is available (i.e. markets with thin information from this point onwards).

In order to verify the capability of such methodologies to represent the actual behaviour of real estate market performances, we apply them to the UK market where a valuation-based index (i.e. namely the IPD index) already exists. However, if we use this term of comparison, we implicitly assume that the IPD index represents “true market returns”. Since we acknowledge the existence of a smoothing issue in valuation-based indices, we also decide to obtain unsmoothed indices adopting standard techniques suggested in the literature. These new series are probably more reflective of the actual market transaction prices and form another basis of comparison for the three indices we propose to measure returns in markets with thin information. We then use differences

⁸ The “Scott time series” is computed by applying the IPD methodology to the data collected from the portfolio of an insurance company – see Scott [1996].

between the comparison of our indices with original and unsmoothed series to draw conclusions upon the impact of smoothing on index construction methodologies.

On one hand our methodologies are data-driven since we need to consider the data types we may be able to obtain in markets with thin information which do not show an historical real estate index. Particularly, we find that two main sources of information could be used:

- share prices and other market/accounting data of real estate vehicles. Such data are easily available where property companies or real estate funds are publicly traded in the stock exchange.
- cash flow data of each individual property. Companies are normally required (by the law or accounting rules) to maintain a record of the purchase price and periodic capital expenditures for each building they own. If a recent (but not necessarily periodic) valuation of these properties is available, regression techniques may be used to obtain the average periodic (i.e. annual) return by comparing initial purchase prices and most recent valuations.

On the other hand, however, our intention is not only to use a data-driven approach, but also to design index construction methodologies carefully, and to incorporate in their application as much market information as possible.

The thesis is structured as follows. Chapter 2 describes main index construction methodologies and presents a literature review of the most important issues arising from each method. We also present examples of current indices available in real estate

markets and highlight significant differences between different providers adopting similar methods.

In chapters 3 and 4 we create a proxy for direct real estate returns, starting from information about real estate vehicles. Chapter 3 adjusts returns of UK property company shares by adopting a Weighted Average Cost of Capital framework (i.e. WACC). Specifically, this method – already applied by Barkham and Geltner [1995] – is updated with new information and for the first time applied to a monthly frequency. A leverage (or gearing) ratio reflecting market rather than book values and coming from primary sources is also used in the analysis.

In chapter 4 we firstly reach three main theoretical findings about the relationship between levered and unlevered beta (i.e. the value of a levered firm equals the value of the same but unlevered company plus a tax shield). Secondly, we suggest a framework to retrieve direct property performances from vehicle-based indices through a Capital Asset Pricing Model net of illiquidity costs (i.e. NCAPM). We then compare our indices with both original and unsmoothed valuation-based returns and test for price discovery between securitised and unsecuritised markets (the empirical analysis uses both annual and monthly returns).

In chapter 5, supported by recent UK results on valuation accuracy, we argue that valuation and prices could be used inter-changeably because there is no systematic error if the overall sample is big enough. We employ individual property data (i.e. initial purchase prices, capital expenditures and most recent valuations) to create four different capital growth indices using two repeated-measures regression techniques (Bailey et al

[1963] and Geltner and Goetzmann [2000]) and two backward looking methods similar to the one IPD adopts with a forward looking view.

Finally, chapter 6 contains a discussion of the overall results obtained using the three index construction methodologies. Particularly, we draw main conclusions about the ability of these indices to represent direct real estate performances in markets with good information flows (i.e. UK market). We then discuss the applicability of these methods to markets with thin information. Finally, we present some ideas for a further development of this research.

Chapter 2

TYPES OF INDICES AND METHODOLOGICAL ISSUES

2.1 INTRODUCTION

Due to a lack of information on transaction prices, several types of performance measures have been developed in real estate markets. The literature on index construction methodologies suggests that each method faces some problems and needs to be adjusted in order to represent true market prices. This section focuses on four main categories into which real estate indices can be grouped:

- *Valuation-based indices* (section 2.2). They represent the main source of information in real estate markets and use capital values rather than transaction prices to represent returns actually achieved by investors.
- *Transaction-based indices* (section 2.3). Three types of measures have been developed by modelling transaction data: hedonic indices employ qualitative information about properties and obtain the “hypothetical value of a standard constant-quality property”; repeated-sales regressions exclusively use transaction prices of properties sold at least twice during the examined period; hybrid methods combine the two previous approaches.
- *Synthetic valuation-based indices* (section 2.4). Publicly available data on market rents and yields are combined to obtain indices measuring portfolio returns. Differently from valuation-based indices these measures represent hypothetical rather than actual portfolio returns.

- *Vehicle-based indices* (section 2.5). They employ data on securitised real estate and they thus represent the performance of vehicles – such as property companies or real estate investment trusts – rather than the one of their underlying property assets. Information on private real estate returns are then obtained by modelling the main factors differentiating the two types of performances.

This chapter contains a literature review of the main methodological issues raised for each type of index. In each of the four sections, we also present a description of the methodology used by main indices currently available in the market.

2.2 VALUATION-BASED INDICES

The most common performance measure developed in property markets uses capital values rather than prices. The total return represents the overall performance achieved by investors owning private real estate. The total return can then be split into two types of returns: capital growth and income return. The capital growth represents the change in capital value net of any capital flow (i.e. expenditures or receipts), divided by the capital employed. The income return is the ratio between the income receivable net of property management and irrecoverable costs, and the capital employed. Section 2.2.3 contains a detailed explanation of the methodology and differences in formulae among

index providers are identified (e.g. the definition of capital employed is different for Investment Property Databank and Jones Lang LaSalle).

Since valuations are used to construct the index, two main issues become relevant: valuation accuracy/consistency and smoothing. The former refers either to the possibility that valuations do not properly reflect prices (i.e. valuation accuracy), or to the fact that appraisals are “subjective” and different valuers may value the same property differently (i.e. valuation consistency). The second issue comes from time series features of valuation-based indices, which tend to show a high degree of autocorrelation and a low volatility, with some theoretical explanation already been tested in the literature. Sections 2.2.1 and 2.2.2 focus on the literature analysing these two issues, while section 2.2.3 contains a description of current valuation-based indices used in the UK and US real estate markets: Investment Property Databank, Jones Lang LaSalle (i.e. JLL) and National Council of Real Estate Investment Fiduciaries.

2.2.1 Valuation accuracy and consistency

The extent to which valuations reflect prices is known in the literature as valuation accuracy and it is strictly linked with the question of whether appraisals can be used to provide measures of market performance.

Brown [1985], IPD/Drivers Jonas [1988, 1990] and Cullen [1990] demonstrate that valuations (on average) reflect prices. They use a sample of properties that have been valued at the end of the year and subsequently sold during the following months. These

papers regress valuations on prices, testing the significance of the intercept (α) and slope (β) of the following equation:

$$price_i = \alpha + \beta * value_i + \varepsilon_i$$

Their basic idea is to test for the intercept and slope being not significantly different respectively from 0 and 1. Another statistical measure they use to support their results is the R^2 . They also remove the problem of change in dimension by working in £/sqf. The only difference between these studies consists of the unit of measures: while Brown uses the logarithm of prices, IPD/Drivers Jonas and Cullen use levels.

An important methodological issue arises from all these studies and has been addressed by Matysiak and Wang [1995] (see also Newell and Kishore [1997] for the same analysis on the Australian market): previous analyses are too poor in terms of diagnostics (e.g. residuals are assumed normal, the standard error is not shown, heteroskedasticity is not tested, etc.) and they do not even look at the problem of valuation accuracy in different phases of the market cycle. The two authors partially restrict previous conclusions verifying that valuation accuracy holds only in stable markets because valuers are slow to incorporate market movements when markets move more rapidly (i.e. slumps and booms). The probability of finding the price within a range of 10%, 15% and 20% above or below the previous valuation is only equal respectively to 30%, 55% and 70%.

The US literature has also studied this issue. For example, Fisher et al [1999] use the NCREIF database to analyse the Absolute Mean Difference as

$\left[\frac{(\text{Price} - \text{Appraised Value})}{\text{Appraised Value}} \right]$ and they reach three main conclusions being consistent

with previous ones:

- Properties on average tend to sell at only a very little premium (2.64%) over the previous valuation figure within a portfolio context (positive and negative differences cancel each other out);
- The absolute mean error remains just a little bit bigger than 10% (with the main concentration in the range 1% to 5%), but this is partially due to the applied methodology: the last valuation is not used and the valuation of two quarters back is rolled forward with an appropriate NPI capital growth (by sector and region);
- The absolute value error peaked in 1991 and 1992 (mainly due to the office sector in a period of a credit crunch in the real estate market). The stability of the market (which varies by property type over time) clearly has an impact on the reliability of appraisals.

All these methodologies compare prices with valuations and analyse the ability of valuers to estimate the *“amount for which a property should exchange on the date of valuation between a willing buyer and a willing seller”*⁹. However, two main issues arise with this approach. Firstly, if the valuer knows that a property will be sold during the following months, he/she may already have some initial information about the transaction which could influence his/her appraisal (if some pieces of information are already incorporated, the actual valuation error may be underestimating the true error

⁹ RICS Appraisal and Valuation Standards (Red Book), 2005.

which would be found for a continuous set of valuations). Moreover, another distortion may be due to the fact that investment managers normally tend to sell a property when they receive an offer they estimate to be above the market value.

These two main issues, along with a need to assess the consistency of valuation practices in real estate markets – i.e. the uniformity of standards between different valuers and then the stability of valuation errors – are behind another stream of literature studying discrepancies between several appraisal values attributed to the same property (both at a specific point in time and throughout time). In other words, the valuation of a particular building is compared with other valuations of the same building made by different valuers, rather than with its subsequent sale price.

Geltner et al [1994] investigate the existence of a purely random component of the disaggregate appraisal error, trying to separate it from a smoothing effect. They concentrate on the appraisal error (i.e. comparison of appraisals with true market values), rather than focusing on the difference between transaction price and valuation, and find a standard error equal to 11.07% included in the range 6%-13% (this result is in line with the ones obtained with a valuation to price methodology).

Diaz [1997] applies a cross-sectional analysis of thirty simultaneous independent appraisals of the same industrial property. He creates two sub-samples of fifteen appraisals each and estimates the average capital value for each sub-sample. He then computes the “valuation error” of each appraisal as the difference of its value from the mean, expressed as a percentage. He obtains a 2.6% standard deviation of the valuation errors for each sub-sample.

Diaz and Wolverton [1998] analyse 31 valuations at two points in time and obtain two sets of values: the first one composed of 16 appraisals and the second one – after 8 months – of 15 appraisals. They study both an anchored (i.e. same valuers doing the appraisal 8 months later) and an unanchored case (i.e. different valuer with no information on the previous valuation available for the second group of 15). The sample standard deviation of the relative appraisal error is 6.90% in the first case and 5.36% in the second one. This result is significantly higher than in Diaz [1997], but the difference is attributable to two main reasons: appraisers come from another region and are not perfectly familiar with the regional market, and the property is an apartment, which is probably more difficult to value than a commercial building.

Finally, Graff and Young [1999] compare internal and external valuations contemporaneously done on 747 properties between 1989 and 1997, and they also test for a constant probability distribution of the random appraisal error across time and sectors (for both empirical evidence is found). In periods of stable markets its standard deviation is equal to 2.0% with a peak of about 5.4% in 1991-1992.

All valuation accuracy/consistency studies find a random appraisal error, whose extent varies across markets and with different market conditions. However, individual property random errors cancel each other out at the index level. The main attention should therefore focus on systematic errors, which may lead to a bias in performance measurement.

2.2.2 Valuation smoothing

The literature defines valuation smoothing as the effect of temporal lagging on periodic returns series. Consequently, smoothing can be easily identified in time series properties of indices, which tend to be cyclical and to show a low volatility and high autocorrelation patterns.

When a portfolio (i.e. index) is considered, three main factors may cause smoothing: the index construction in itself (i.e. temporal aggregation of individual appraisals referring to different dates), valuations not done at each measurement interval (i.e. stale appraisal), and the tendency valuers have to change their valuation figures from one period to another only if the change is greater than a specific threshold (e.g. new monthly values tend to be reported equal to previous ones if they have not increased by at least 1% or 2%). At an individual property level, instead, the problem arises because valuations are based on comparable sales (i.e. comps) and the valuer tends to use more than one comparable (and they are lagged over time).

Geltner et al [2003] provide a useful discussion of theoretical models used to create unsmoothed versions of valuation-based returns. They conclude that reverse engineering and econometric models are the two major approaches currently used to address the appraisal smoothing issue and to “re-construct” transaction-based indices.

Main theoretical models – and relative empirical applications – can be categorized into two main groups: models used to define and detect smoothing at either the portfolio or individual property level, and techniques used to obtain unsmoothed valuation-based

returns. The rest of section 2.2.2 presents a literature review of the main studies in these two areas.

2.2.2.1 Individual property vs. portfolio level

Some papers analyse the smoothing issue at an *individual appraisal level*.

Geltner [1997] states three basic rules to be followed by valuers when valuing properties:

1. *“In a world with a single point in time, the appraiser should use as many comparable sales as possible”* because the average of transaction prices can be considered an unbiased estimate of the true market value;
2. *“In the real temporal world, a finite number of comps will be optimal as the appraiser must balance the advantage of a larger number of comps with the disadvantage of drawing comps from farther in the past”* because there exists a trade-off between a pure random error – due to a small sample size for comparables – and a systematic bias – linked to a big sample size leading to an increasing number of observations containing old information;
3. *“When the appraisal of an individual property is to be used in the construction of an aggregate value, only the most recent comp should be used”* because purely random errors tend to cancel each other out and only the systematic component of the error remains in a portfolio context.

Valuation smoothing then represents the systematic past market value bias (i.e. the use of past comparables to value properties in a portfolio context) on the current valuation. This problem is most significant when transactions are infrequent – because the period between the first and the most recent comparable is longer – and when the real estate market moves faster – because the difference of prices between the first and the most recent comparable is wider.

Bowles et al [2001] extend these findings and use sampling theory:

- to measure confidence intervals for portfolio valuation errors;
- to define the minimum number of properties necessary to achieve a pre-fixed level of accuracy at a portfolio level;
- to compute portfolio valuation errors for a range of combinations of individual errors and included number of properties;
- to study the behaviour of valuation error and its confidence intervals when the size of the portfolio is increased (they both tend to diminish).

Clayton et al [2001] move on from Geltner [1989, 1997]'s findings and study appraisal smoothing caused by a temporal lag bias due to valuers using past information on transaction prices. They analyse two Canadian portfolios with a full set of valuation assumptions including comparable sales at an individual property level over a ten years period (1986-1996). The basic model is expressed by $V_t^* = c + \beta * V_t + \omega * V_{t-1}^* + \varepsilon_t$, where V_t^* is the appraised value at time t , and V_t is the price of the contemporaneous comparable sale (i.e. it is assumed to be the estimate of true market value). They run a

slightly modified version $\frac{V_t^*}{V_{t-1}^*} = \omega + \beta * \left(\frac{V_t}{V_{t-1}} \right) + \varepsilon_t$, and jointly test for β and ω being respectively equal to 1 and 0 (i.e. if a temporal lag bias is found the two coefficients would be both positive and less than 1). The estimated coefficients are respectively equal to 0.815 and 0.175 that represent the weights valuers put on new and old information. Finally, when the sample is split into anchored and unanchored worlds, the weight on newer information is also found to decrease when the same valuer is responsible for the two valuations (at both time t and $t-1$), passing from 0.870 to 0.689.

Other studies analyse valuation smoothing at a *portfolio level*.

Geltner [1993a] considers this issue by analysing the temporal aggregation effect, i.e. the use of several spot valuations occurring over a period of time to produce a property portfolio (i.e. index) value at a single point in time (e.g. the use of valuations of 50 properties appraised between September and December to compute a portfolio figure referred to December). He finds that this type of smoothing reduces portfolio variance and beta respectively by 33% and 50%.

By proposing a financial technique developed by several authors – Bailey et al. [1963], Case and Shiller [1987], Clapp and Giaccotto [1992] and Gatzlaff and Haurin [1996] – Geltner [1999] studies the smoothing issue coming from stale appraisal, which happens when properties show values not exactly referring to the performance measurement date (i.e. month or quarter). When there is no appraisal at that point in time, they are assumed to be equal to previous figures and subsequent zero capital growth rates

dampen the extent of the overall capital appreciation down (or up if the market one is negative). To solve this problem, Geltner [1999] suggests the use of a repeated measures regression that minimises the sum of the squared errors (i.e. simple least squares model). This regression is based only on appraisals whose value has changed or been explicitly updated since the previous measurement. The RMR index is found to be a leading indicator of the valuation-based index and shows less seasonality and less tendency to peak constantly on the twelfth month (or fourth quarter) than the appraisal based-index.

Finally, Bond and Hwang [2005] identify three sources of lower volatility (smoothing, nonsynchronous appraisal and cross-sectional aggregation) by applying an ARFIMA process, where the long memory parameter (FI) explains the level of smoothing (empirically found to be less than previous studies), the MA parameter sheds light upon the nonsynchronous appraisals (worse for higher frequencies) and the AR parameter reflects cross-sectional aggregation issues. Finally, they find this model to perform better than simple AR or ARMA models previously suggested in the literature.

2.2.2.2 Unsmoothing techniques

Quan and Quigley [1991] were the first to analyse smoothing related to the functioning of real estate markets and transaction noise. They assume a random walk process for transaction prices, with valuers using an updating rule for their appraisals on the base of a set of comparables and the last period's prediction error (weighted). With k , P_t^* and

P_t^T indicating respectively the weight assigned to new information, the appraiser's estimate of the market price (i.e. valuation) at time t , and its true estimate at time t , the valuation process at a market level follows the path: $P_t^* = k * P_t^T + (1 - k) * P_{t-1}^*$. They finally apply it to returns rather than levels, following on from Geltner [1989]'s model. Geltner [1993b] proposes a model to extract underlying market returns from smoothed ones without strongly assuming true returns with no autocorrelation. This approach (known as first-order autoregressive reverse filter) allows for unsmoothing through "judgmentally estimated parameters" at both aggregate and individual property level. The result is a series of returns with much higher standard deviation (between 6.9% and 10.3% depending upon the index and parameter used), and lower positive autocorrelation (between 0.16 and 0.40).

Fisher, Geltner and Webb¹⁰ [1994] apply the previous model as well as the more general Quan and Quigley's one to derive respectively a "market value index" and a "full-information value index". In the second model, they impose an additional condition: the "true volatility" of commercial property valuation-based returns is approximately half the volatility of the stock market (e.g. S&P500), i.e. double the volatility smoothed returns show. As they use quarterly returns, in addition to the first-order parameter (Quan and Quigley), there is also a strong a-priori case for a fourth-order lag to allow for seasonality. They then run an autoregressive process of order four and use the

volatility of the residuals to compute: $w_0 = \frac{2 * \sigma_{resid}}{\sigma_{equity}}$. They then obtain the true return

¹⁰ FGW.

from $r_t = \frac{(r_t^* - \phi(B)r_{t-1}^*)}{w_0}$, where r_t^* represents the smoothed return at time t , $\phi(B)$ is a lag

operator of order four, and w_0 indicates the weight assigned to the new information.

Chaplin [1997] develops an unsmoothing model allowing for shifts in the parameter depending upon the actual growth state (i.e. he assumes a non-constant ratio between variances of valuation noise and variances of market noise). Chaplin also introduces a double unsmoothing process to work out transformed series for both capital growth and income return for the CB Hillier Parker (or CBHP) synthetic index (i.e. ERV and yields). He concludes that his transformed series produces a better estimate of transaction prices, showing a double correlation coefficient with FTSE index and a more than double beta if compared with the smoothed series.

Brown and Matysiak [1998] pass from an aggregate to an individual property level and propose a time-varying approach to estimate the smoothing parameter of a sample of 30 properties valued monthly between December 1986 and October 1995. By applying maximum likelihood estimation and a Kalman filter, they find a time-dependent smoothing parameter (weight to new information) ranging from 50% to 62%, with an average of 57%.

Wang [1998] uses a co-integration approach to derive a long-run unsmoothing parameter from a series of other variables, rather than from past values of the same index. He considers the relationship between direct and indirect property indices, and estimates α from the cointegration model. Firstly, he runs a cointegration regression between a variable fundamentally related with real estate and a valuation-based index:

$\gamma * S_t - P_{a,t-1} = \mu_t$, where S_t represents the value of the chosen economic variable (i.e. FTSE real estate index) at time t and $P_{a,t}$ is the level of the valuation-based index at time t . Secondly, he finds the unsmoothing coefficient being equal to 0.62 (IPD monthly index) and 0.41 (JLL quarterly index) by regressing the return of the valuation-based index at time t ($\Delta P_{a,t}$) on residuals obtained from the previous equation:

$$\mu_t = \frac{1}{\alpha} * \Delta P_{a,t} + v_t.$$

Geltner and Goetzmann [2000] extend Geltner [1993b]'s model by applying the RMR technique to obtain a total return index and not only a capital growth one. They then study twenty years of returns, comparing the time series properties of the two indices (i.e. valuation-based and RMR-based). Secondly, they compare the new index with the one computed by the National Association of Real Estate Investment Trusts (i.e. NAREIT). They find that, still based on valuations, the RMR index tends to lag the vehicle based one. Finally, the new performance measure is used to estimate the amplitude (found equal to 10%) of the purely random error for individual properties.

Cho et al [2003] propose a simple extension to the FGW model to discover the underlying market values from a smoothed valuation-based index without assuming an efficient market. They simply use a generalised-difference specification (i.e. differences in returns are used instead of returns) and justify this solution with three main arguments: firstly the error term now shows zero mean and constant variance (but this is by definition equal to zero and it is also true in Geltner's model); secondly there is not any term on both sides of the equation (i.e. r_{t-1}); finally it is possible to control for non-

stationarities. However, this procedure seems redundant because returns are already stationary and do not need to be differentiated.

2.2.2.3 Concluding remarks

So far we have seen that finance theory identifies several causes underpinning the smoothing issue in real estate valuation-based indices. Moreover, it suggests that smoothing is an extremely important issue on theoretical grounds. This argument is confirmed with supporting empirical evidence, which finds volatility underestimation and high autocorrelation patterns, in contrast with empirical evidence from other asset classes, such as bonds and equities.

However, valuation-based indices do not necessarily need to be unsmoothed for all purposes. Smoothed valuation-based indices, for example, are suitable for benchmarking purposes, where a comparison between performances of long-term investment is needed. Nevertheless, when the index is used for forecasting, or as the underlying asset for derivatives, unsmoothed versions should be preferred because they are more likely to follow transaction prices movements.

The issue of unsmoothing becomes also highly relevant to markets with thin information for two main reasons. First, we need to test the three index construction methodologies that we develop in chapters 3, 4 and 5 against the current valuation-based index in the UK market, where relevant information is available. For some purposes the relationship with raw valuation-based index data may be relevant, while

for other purposes the relationship with unsmoothed indices should be preferred. Secondly, in a market with valuation information only (i.e. where transaction-based data are not available), unsmoothing may be important to obtain indices that reflect underlying transaction prices.

Since the literature suggests several ways to adjust valuation-based returns, in chapter 3 we apply different unsmoothing methods to our data in order to see the impact of each model (and the chosen unsmoothing parameter) on the return distribution.

2.2.3 Current valuation-based indices

2.2.3.1 Investment Property Databank methodology

Investment Property Databank is the most important provider of real estate indices throughout Europe and probably the entire world (see table 2.1 for reference on start date and market coverage). This company produces indices measuring property returns in order to achieve a double aim: to provide “indicators of market performance for industry commentators and players”, and to create a benchmark (or several benchmarks) to be used by portfolio managers willing to compare their investment performances.

Table 2.1: Start date and market coverage of IPD indices¹¹

Country	Start date	2004 Total Return	No. of properties	Total Value €billion	Est % of Market ¹
Canada	1984	12.9	1,679	29.8	50%
Denmark	2000	6.3	1,319	9.3	39%
France	1986	10.1	5,723	65	52%
Germany	1996	1.3	3,490	61.1	30%
Ireland	1984	11.5	321	3.8	79%
Italy	2002	9.5	469	7.5	15%
KTI Finland ²	1998	5.6	3,008	15.8	60%
Netherlands	1995	7.7	6,243	39.6	60%
Norway	2000	10.4	529	8.7	42%
Portugal	2000	10.6	547	6.9	60%
Spain	2001	11.5	527	10.5	44%
South Africa	1995	23.4	2,232	9.4	60%
Sweden	1984	5.8	934	16.2	30%
Switzerland	2002	4.9	3,024	23.7	30%
UK	1971	18.3	10,986	170.6	45%
Total			41031	477.9	

1 Total asset value of institutions & listed vehicles

2 Through 'compliance' agreement with KTI (Finnish Institute of Real Estate Economics)

IPD indices are valuation-based indices and include properties both directly and indirectly owned by its clients (in the UK the coverage is around 45% of the total asset value of institutions and listed vehicles). However, market measures, as opposed to portfolio measures, only include standing investments (i.e. properties held throughout the year) which show main required data (e.g. rent, costs, etc.), a capital growth which is not abnormal, and values obtained through a standard valuation method. The impact of transactions and developments on portfolio returns is separately provided.

¹¹ Source: Investment Property Databank, 2005.

The starting date of the UK IPD index is 1971, but 1981 should be considered the real base date because figures referring to the 1970s reflect the performance of properties owned by a very low number of funds (i.e. the index is not representative of the market)¹².

Since 2001, IPD performance measures have been re-computed to reflect a monthly time-weighting structure (i.e. indices weight capital inflows/outflows during the period, by considering the timing at which they happen) and to align property performance to other asset classes returns – equity and bond markets normally use the same method with a daily or intra-daily frequency. However, the changes in the methodology did not cause a significant difference in recorded performance (i.e. the biggest spread was 30 basis points on a yearly basis). In order to use a TWRR methodology monthly, if valuations do not exist with such a frequency (i.e. only annual or quarterly appraisals are available), IPD computes monthly values by interpolating between either annual or quarterly figures.

¹² In the early 1970s only data of properties owned by eight funds were available (Source: Investment Property Databank).

Table 2.2: Sector and regional components¹³ (as at the end of 2004)

	2004 Total Return	No of Properties	Total Capital Value £m	% Total Capital Value
All Retail	20.5	4,358	64,408	53.3%
Standard Shops	21.1	2,639	15,711	13.0%
Central London	17.9	298	3,717	3.1%
Rest of London	23.7	296	1,450	1.2%
South East & Eastern	22.6	650	2,801	2.3%
Rest of UK	21.8	1,395	7,743	6.4%
Shopping Centres	17.4	312	24,442	20.2%
Retail Warehouses	23.4	1,048	21,713	18.0%
Other Retail	20.9	359	2,542	2.1%
All Office	15.2	2,947	33,273	27.6%
Standard Offices	15.7	2,576	27,853	23.1%
Central London	16.0	1,032	15,062	12.5%
Rest of London	16.4	253	2,675	2.2%
Inner South Eastern	14.3	455	3,610	3.0%
Outer South Eastern	16.8	225	1,285	1.1%
Rest of UK	15.6	611	5,220	4.3%
Office Parks	12.2	371	5,420	4.5%
All Industrial	16.9	2,966	19,298	16.0%
Standard Industrials	17.1	2,636	15,888	13.2%
London	17.3	378	3,369	2.8%
Inner South Eastern	15.2	349	2,790	2.3%
Outer South Eastern	17.4	505	2,933	2.4%
Rest of UK	17.6	1,404	6,796	5.6%
Distribution Warehouses	16.0	330	3,409	2.8%
Other Property	17.3	715	3,782	3.1%
All Property	18.3	10,986	120,760	100%

Table 2.2 shows the composition of the IPD sample by sectors and regions (as percentage of capital values) at the end of December 2004. Retail and office sectors make up 80.9% of the “total market”, leaving only 16.0% to industrial estates and the remaining 3.1% to a mix of farms, leisure and residential properties. The regional

¹³ Source: Investment Property Databank, 2005.

composition depends upon the sector, but Greater London constitutes one third of total standing investments. Central London is the predominant region for offices, whilst retail properties are concentrated in Wales and the North of England.

Table 2.3: IPD Annual Index composition by investor type¹⁴ (31 December 2004)

Investor Type	No of Properties	Capital Value (£bn)
Insurance Funds	4,948	57.21
<i>Insurance funds</i>	2,335	40.76
<i>Unit-linked funds</i>	1,976	11.67
<i>Managed funds</i>	637	4.77
Segregated Pension Funds	2,625	24.32
Property Companies	390	10.15
Property Unit Trusts	981	11.95
Traditional Estates	651	3.37
Other types	1,391	13.76
Total	10,986	120.76

At the end of December 2004, the IPD databank includes 10,986 properties, belonging to at least 250 portfolios and worth £120.76 billion: more than £80 billion are owned by insurance funds (insurance companies, unit-linked funds and managed pension funds) and segregated pension funds, and £10 billion by property companies – see table 2.3.

¹⁴ Source: Investment Property Databank, 2005.

The main measure of performance is the total return, which reflects the return investors achieve by directly investing in real estate throughout the measurement period. The following measure represents the old formula used by IPD to compute the total return:

$$TR_i = \frac{\sum_{t=1}^n (CV_{i,t} - CV_{i,(t-1)} - P_{i,t} + S_{i,t} - C_{i,t} + NI_{i,t})}{\sum_{t=1}^n \left(CV_{i,(t-1)} + P_{i,t} + \frac{1}{2}C_{i,t} - \frac{1}{2}NI_{i,t} \right)}$$

where

$CV_{i,t}$ = Capital Value of Property i at time t

$C_{i,t}$ = CapEx for Property i at time t

$NI_{i,t}$ = Net Income of Property i at time t

$P_{i,t}$ = Purchase Price for Property i at time t

$S_{i,t}$ = Sale Price for Property i at time t

However, since the end of 2004, the denominator of this measure has been changed to reflect the monthly structure of the TWRR computation, with the new formula showing two main differences.

Firstly there is no more distinction between major and minor capital expenditure. Previously, only expenses in excess of 20% of the capital value were considered capital expenditures (with other expenses included in operating costs and directly deducted from the gross income). However, this threshold raised three main issues: its value was arbitrarily chosen (e.g. why 20% and not 10% or 30%?), the treatment of expenses above and below it was inconsistent and the threshold complicated the data collection process.

Secondly, the net income is no longer deducted from the denominator. Its deduction was required by the old money-weighted formula to assume a continuous reinvestment of income. However, with a time weighted structure there is no need to make this adjustment anymore since the reinvestment of the income is already implicit at least with a monthly frequency (i.e. monthly returns are compounded to obtain the annual return).

Consequently, the new formula employed by IPD is as follows:

$$TR_t = \frac{\sum_{i=1}^n (CV_{i,t} - CV_{i,(t-1)} - P_{i,t} + S_{i,t} - C_{i,t} + NI_{it})}{\sum_{i=1}^n (CV_{i,(t-1)} + P_{i,t} + C_{i,t})}$$

Table 2.4 shows the impact of these changes on annual figures. The difference between returns obtained with either the old or the new methodology is not significant for any year and is always within 10 basis points on an annual basis.

Table 2.4: Impact of changes in the main formula¹⁵

	Total Return			Capital Growth		
	Old	New	Diff.	Old	New	Diff.
1994	12.3	12.3	0.0	4.7	4.6	0.0
1995	4.6	4.5	0.0	-2.7	-2.7	0.0
1996	10.9	10.8	0.0	3.1	3.1	0.0
1997	17.7	17.7	-0.1	10.0	10.0	0.0
1998	12.2	12.1	0.0	5.3	5.3	0.0
1999	15.0	15.0	-0.1	8.1	8.1	0.0
2000	11.4	11.3	0.0	4.8	4.8	0.0
2001	7.1	7.0	0.0	0.6	0.6	0.0
2002	9.6	9.6	0.0	2.9	2.9	0.0
2003	10.7	10.6	0.0	4.0	4.0	0.0
Annualised figures						
23yr	10.3	10.3	0.0	3.7	3.7	0.0
20yr	10.4	10.3	0.0	3.6	3.5	0.0
10yr	11.1	11.0	0.0	4.0	4.0	0.0
5yr	10.7	10.7	0.0	4.1	4.1	0.0
3yr	9.1	9.1	0.0	2.5	2.5	0.0

Even if we acknowledge the need to make some simplifying assumptions because of the high number of observations involved (more than 100 fields for each property are collected), it is important to highlight some pitfalls which arise from these assumptions:

1. The decision to compound monthly returns assumes the reinvestment of cash flows with a monthly frequency, notwithstanding the current lease structure which is based on rents paid quarterly in advance;

¹⁵ Source: Investment Property Databank, 2005.

2. Indirect costs at a portfolio level (e.g. company taxation, portfolio management, etc.) are not considered. Consequently, the total return of direct investment real estate is not automatically comparable with the return of equity or bond investments due to the higher management costs involved in property markets;
3. The computation of a continuous return $[ret_t = \log(index_t) - \log(index_{t-1})]$ would not be consistent with the discrete method used to produce the index. A continuous return is useful for finance studies and is often used in research. However, time series properties of returns will not be affected.
4. For frequencies higher than the annual one, values do not tend to reflect price movements. This is mainly due to an inertia in changing appraisal assumptions, which determines an adjustment to values made only if minimum threshold is passed (e.g. other parameters being constant, the valuer may decide not to change the yield until it moves by 0.25, even if a movement of 0.125 would be reflected in a different capital value).

So far we have considered performance measures based on the IPD universe, which include both transactions and developments. However, when IPD produces market returns, it uses standing investments only. Standing investments are defined as properties which are completely constructed and lettable for the whole analysis period. From this point onwards, when we speak about real estate returns, we refer to returns obtained by standing investments only.

The formula measuring the performance of this type of properties is computed as follows:

$$TR_t = \frac{\sum_{i=1}^n (CV_{i,t} - CV_{i,(t-1)} - C_{i,t} + NI_{it})}{\sum_{i=1}^n (CV_{i,(t-1)} + C_{i,t})}$$

IPD returns are net of all non-recoverable operating costs and capital expenditures (i.e. capital improvements, transaction costs, maintenance expenses, property management fees, etc.), but they are gross of all costs incurred at a portfolio level (i.e. portfolio management fees, financial expenses and fiscal costs).

The total return can be attributed to two main components:

- Capital growth (difference in value over the period net of capital expenditure, divided by capital employed, i.e. percentage change of portfolio value), and
- Income return (i.e. income net of non-recoverable operating costs as a percentage of capital employed):

$$CG_t = \frac{\sum_{i=1}^n (CV_{i,t} - CV_{i,(t-1)} - C_{i,t})}{\sum_{i=1}^n (CV_{i,(t-1)} + C_{i,t})}$$

and

$$IR_t = \frac{\sum_{i=1}^n NI_{i,t}}{\sum_{i=1}^n (CV_{i,(t-1)} + C_{i,t})}$$

If the capital value is expressed by the ratio between the OMRV and the yield (i.e. rent in perpetuity), the capital growth in year t can also be explored to discover if the growth is due to a rental growth in the same year $\left[\frac{OMRV_t - OMRV_{t-1}}{OMRV_{t-1}} \right]$ – directly proportional – and/or to a yield shift $\left[\frac{y_t - y_{t-1}}{y_{t-1}} \right]$ – inversely proportional.

Similarly, the income return can be driven by a change in both/either gross income and/or the cost structure.

2.2.3.2 Jones Lang LaSalle methodology

Jones Lang LaSalle (JLL) replaced LaSalle Asset Management (LAM) for the construction of in-house real estate indices. Their base date is June 1977 and they are updated quarterly (i.e. March, June, September, December). The sample is much smaller than the one used by IPD because it includes only properties that are directly managed by Jones Lang LaSalle. However, when JLL took over the construction of LAM Indices, the number of properties drastically increased from between 152 and 200 before 2001Q3 to more than 800 in 2001Q4. At the moment 19 funds are included in the database used to compute performance measures (compared with IPD's 250 funds). As for all UK property indices, no sampling methodology is applied and all properties within the valuation database are included if they:

- represent standing investments (i.e. developments are excluded)

- are not owner occupied;
- are valued at both the beginning and the end of the performance interval (i.e. transactions are excluded).

Properties included in the database belong only to office, retail and industrial sectors, as defined by IPD. The geographical composition of the sample also follows the IPD classification. The weightings for both each sector and each region are kept within a +/- 5% range from the ones shown in the latest Property Investor Digest. Consequently, by looking at the sector by region matrix, the weightings will match those of IPD +/- 3% (e.g. the weighting of JLL South East Industrial is included in the range [IPD South East Industrial - 3%; IPD South East Industrial +3%]). If the sample is not naturally weighted within those limits, some properties are randomly deleted from the sample until weights match up. However, a maximum of 10 properties can be deleted in each sector by region sub-sample.

The total return for quarter q is simply computed as the sum of capital growth (first part of the equation) and income return (gross of management costs):

$$TR_q = \frac{\sum_{i=1}^n (CV_{i,q} - CV_{i,(q-1)} + NI_{iq})}{\sum_{i=1}^n CV_{i,(q-1)}}$$

where

$CV_{i,q}$ = Capital Value of Property i at the end of quarter q

$NI_{i,q}$ = Net Income of Property i at time t with

$$NI_{i,q} = \frac{ANI_{iq}}{4} \text{ (i.e. Annual Net Income at quarter q divided by 4)}$$

This formula represents an even more simplified version of the one used by IPD and it does not deal with management costs and voids too. Moreover, it represents a holding period return formula (i.e. MWRR) and, consequently, it does not eliminate the distorting effects of inflows/outflows during the period.

The same methodology is applied to JLL *value and growth indices*, reporting the performance of properties with similar characteristics. These measures represent a novelty for real estate markets and a precious tool to reach better investment management decisions and asset allocation choices (i.e. a more precise and efficacious style analysis to attribute portfolio performances and to create a benchmark index). JLL style indices are based on 826 properties, but the number of properties used within the sample in any one quarter is lower than that (i.e. only properties showing an income during the interval and valuations at both the end and the beginning of the quarter are included). In order to achieve a larger sample size, the style indices are not currently weighted by region or sector. The “sample” is split (by equivalent yield) into two separate sub-samples, measuring the performance of growth and value properties – respectively low and high yielding estates. Three main measures are computed: total return, capital growth and net income.

2.2.3.3 NCREIF methodology

Although the official beginning of the National Council of Real Estate Investment Fiduciaries (NCREIF) is dated at the beginning of 1980s, the work of creating a US real

estate index began in the late 1970s, when 14 investment managers agreed to form a not-for-profit entity (i.e. a feature distinguishing it from IPD) to promote real estate research. A database containing operating information at an individual property level is used to produce a valuation-based index, where each market value is determined by a real estate appraisal methodology, which is consistently applied (see Real Estate Information Standards [2003]).

The NCREIF Property Index consists of both equity and geared properties, but levered properties are reported on a degeared basis. So, the Index is completely unlevered. The database only includes actual income-producing properties (i.e. no developments) that belong to four main sectors: apartment, industrial, office and retail. They are all investment-grade, and have been purchased on behalf of tax-exempt institutions and held in a fiduciary environment. Sold properties are removed from the index, but the historical information remains in the database.

The value of the Index is set at 100 in 1977, fourth quarter. Quarterly returns of individual properties are computed before deduction of asset management fees and weighted by their market values at the index aggregation level.

Three main performance measures are computed. Capital appreciation (i.e. capital growth, CG_t) shows the change in market value net of any capital improvements/expenditures and partial sales, as a percentage of the average quarterly capital employed:

$$CG_t = \frac{(MV_t - MV_{t-1}) - CE_t + PS_t}{MV_{t-1} + \frac{1}{2}CE_t - \frac{1}{2}PS_t - \frac{1}{3}NOI_t}$$

where MV_t represents the market value at the end of quarter t , CE_t , PS_t and NOI_t respectively refer to capital expenditures, partial sales and net operating income in quarter t .

The income return (IR_t) measures the performance achieved through “ordinary management” and it is obtained as the ratio between net operating income (NOI_t) and average capital employed:

$$IR_t = \frac{NOI_t}{MV_{t-1} + \frac{1}{2}CE_t - \frac{1}{2}PS_t - \frac{1}{3}NOI_t}$$

The total return (TR_t) represents the sum of the two previous measures and is expressed as follows:

$$TR_t = \frac{(MV_t - MV_{t-1}) - CE_t + PS_t + NOI_t}{MV_{t-1} + \frac{1}{2}CE_t - \frac{1}{2}PS_t - \frac{1}{3}NOI_t}$$

Finally, a time-weighted rate of return structure is used to obtain annual (by compounding quarterly rates) and annualised (through a geometric mean) figures.

2.3 TRANSACTION-BASED INDICES¹⁶

In the UK market, the average holding period of a property is ten years¹⁷. Consequently the use of transaction data to construct real estate indices requires the application of econometric techniques because the price of the same “good” is not available at each measurement point (e.g. one year, one quarter, or one month). At each interval, the sample of exchanged properties is in fact different, and this represents the main reason why econometric techniques have to be applied to obtain periodic performances from multi-period returns (as opposed to valuation-based indices, which face smoothing and valuation accuracy/consistency).

In equity markets the existence of a continuously changing sample does not represent an issue because company shares are equal proportions of the same investment and are frequently traded in the stock exchange. Instead, in real estate markets, each asset (i.e. building) is heterogeneous and indivisible, and when transaction prices are used to produce a property index, the quality of properties included in subsequent samples may differ. Consequently, the measurement of returns may reflect the impact of changes in the average quality of traded properties and not only the “real” change in prices. As an example, we could consider the residential market. Let us assume that in 2004 the average house sold in the market has two bathrooms. If the average house sold in 2003

¹⁶ Another version of the material in this section was published in Booth and Marcato [2004a].

¹⁷ Source: Investment Property Databank, 2005.

had only one bathroom, the increased price may be due to the better quality of the property and not to a “genuine” change in the housing price.

In order to overcome this measurement problem (i.e. consistent sample over time), two main methodologies have been applied. The hedonic modelling approach measures the change of the price of a “standard property” – possibly in each segment – and uses extensive information (i.e. transaction price and significant qualitative characteristics) for each traded property. On the other hand, the repeated-sales regression method estimates returns from properties transacted at least twice during the overall historical period. The “link” between the two prices (i.e. multi-period return) and the time series of all cash in/outflows of each property (i.e. panel data) will determine the performance of the overall market and its segments.

So far, transaction-based indices have been developed only for residential markets in the UK. Moreover, the only methodology used is the hedonic modelling approach. However, in the last few months IPD has started an initial investigation to test for the applicability of both these methods to commercial real estate data.

This section contains a brief explanation of the two main methodologies applied to transaction data. No extensive literature review has been done on hedonic modelling because the difficulty of collecting (or unavailability of) a database containing qualitative features of properties over time undermines the applicability of such methods to construct historical indices in markets with thin information.

However, a slightly amended version of the repeated-sales regression methodology using the acquisition price and most recent valuation – rather than two transaction prices

(see section 2.3.4) – of each property could be used because it requires a set of information easily obtainable from primary sources. In chapter 5 we also test the ability of these methodologies to create historical real estate indices for the UK market.

2.3.1 Hedonic Modelling

A possible solution to the problem of a continuously changing sample has been developed in the literature by trying to create a measure for the pricing of a “standard property” (i.e. constant-quality index). In other words the main driving characteristics of property prices are used to retrieve the “true” price movement, which becomes the measure of a property price index.

In order to explain the hedonic approach we use the example of the Halifax residential index in the UK (see section 2.3.5.1). A regression equation is fitted for the relationship between the price of houses and main quantitative and qualitative characteristics. Some of the features are linear variables (e.g. number of bathrooms) and others are represented using dummy variables (e.g. location attributes). Thus we can write the price of house i as:

$$P_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \dots + b_j X_{ji} + e_i$$

where j represents the number of characteristics and n is the number of houses so that $i = (1, 2, \dots, n)$. The explanation of this simple hedonic equation is as follows: the value

(price) of house i comes from a set of j characteristics. Given the information about the j characteristics for each one of the n houses, it is possible to estimate the parameters b_0 to b_j therefore enabling us to derive the hypothetical value of a house with any combination of characteristics at any time. The parameters b_i are computed using ordinary least squares. The functional form for the Halifax index uses the log of the price as dependent variable, and it can then be written as:

$$\ln P_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \dots + b_j X_{ji} + e_i$$

There are several ways of considering the methodology used to calculate the index from the parameters. One way is to think about determining an index that measures the value of a representative house over time. Clearly, the representative house must have the same characteristics between two index dates. However, because many of the j characteristics are dummy variables, it is easier to think in terms of the index value tracking the value of a portfolio of houses. Information on the characteristics of houses bought in 1983 was used to set the weights for the index. Each of the X values is weighted to reflect the characteristics of the houses bought in 1983. The parameters are estimated from the data, and the index value reflects the change in the value of houses with 1983 characteristics between the base date and the date at which the index is calculated.

The weights are given the notation Q in Fleming and Nellis [1984], and thus the value of the index would be represented as follows:

$$I_t = \frac{\text{antilog} \sum b_{jt} Q_{j1983}}{\text{antilog} \sum b_{j1983} Q_{j1983}} \times 100$$

There are three main issues related to this type of indices:

- Coefficients instability over time: it would be better if the weights were regularly updated to produce a chain-weighted index based on characteristics that are closer to those of the average house at the time the index is computed.
- Omitted variables: the model can never capture all the subjective characteristics that determine the value of a property.
- Functional form. The particular model described here considers the value of a house as being a linear and additive function of the characteristics with no interaction between the characteristics. For example a 50 square feet terrace would make the same contribution to the value of a one-bedroom house as it would to the value of a five-bedroom house. Such a linear additive approach may well be unrealistic.

The second problem could be regarded as being a greater problem for commercial properties than for residential properties as, in the former, the number of characteristics and variety of characteristics is likely to be greater. Hedonic modelling has, however, been applied to countries where commercial real estate tends to have more uniform characteristics (such as Singapore). Finally, the other two issues could be overcome

with more sophisticated modelling techniques (i.e. non-linear relationships and time-varying parameters).

So far several model specifications have been used in the literature. Some examples are given below.

Mills and Simenauer [1996] estimate constant quality dwelling prices for four regions of the USA. They use a national database for the first time and then start to face the issue of regional differences in quality pricing. They conclude that more than half of dwelling price increases during the period 1986-1992 was due to quality improvements in dwellings.

Goodman and Thibodeau [1995] demonstrate the presence of heteroskedasticity in hedonic house price indices due to the dwelling age of sampled properties. They apply a semi log equation and estimate parameters with four different dwelling age specifications (i.e. to the power of 1, 2, 3 and 4) and two alternative living areas in sqf (i.e. to the power of 1 and 2). They then use the Goldfeld and Quandt test and the White test to check for heteroskedasticity in the residuals.

Wolverton and Senteza [2000] critique the National Association of Realtors (NAR) house price index because it shows an average change in price without considering either quality or regional changes in the month to month sample. In particular, they employ a hedonic approach replicating the Mills and Simenauer study, and apply a multiple Chow test to check for differences in quality pricing between regions, which they find being significant at 1% level.

Munneke and Slade [2001] apply three time-varying parameter approaches (i.e. quality pricing may change over time) and find instability in coefficients, suggesting the usefulness of these techniques as opposed to constant-parameter models. Little evidence of a selection bias due to the limited number of transacted properties available at each measurement point in time is also found.

2.3.2 Repeated-Sales Regression

If hedonic transaction-based indices have been mainly created for residential markets and just in few cases for commercial ones, the repeated-sales regression methodology (i.e. RSR from this point onwards) has been employed for commercial property more extensively.

The RSR method uses a sample of properties that have been transacted at least twice during the overall measurement period (i.e. at any point in time between the start date and the end date of the index). Several model specifications have been developed in the literature.

The original one by Bailey et al. [1963] finds out periodic returns from the difference of log-prices in time¹⁸. If P_t represents the house price at time t , then the capital growth rate β_t is found from a system of individual property equations as follows:

$$\log\left(\frac{P_{t+s}}{P_t}\right) = \log\left[\prod_{i=t}^{t+s} (1 + \beta_i)\right] = \sum_{i=t}^{t+s} \log(1 + \beta_i)$$

¹⁸ From now on, we will refer to the BMN model.

This can be expressed through the following regression equation:

$$Y = D\beta + \varepsilon$$

where Y represents a vector of relative log-price observations, β is the estimated vector of capital growth and D is a (N x M) dummy variable matrix with N and M indicating respectively the number of properties included in the sample and the number of years used to compute the index. By regressing the dummy variables on the log ratio, the vector β can be estimated. The set of capital growth rates gives the repeated-sales index.

A more detailed explanation (through a simple example) is included in section 5.2.1.

In its original form, a RSR index does not require any estimation of implicit prices of qualitative characteristics (e.g. no. of floors, age, etc.) and then avoids complications associated with the application of hedonic models: selection of variables (i.e. omitted variables issue) and specification of the functional form (i.e. linearity vs. non-linearity). However, this method does have some shortcomings, the most important one being a sample selection bias. Most databanks of real estate prices include a very low percentage of properties transacted at least twice along the measurement period, and this issue is even more problematic when a short time horizon is used for the analysis (i.e. nowadays each property is transacted every ten years on average¹⁹). This means that the sample may represent a very small proportion of up-to-date transaction prices, and most of all, only a specific segment of the market (i.e. more frequently transacted properties would probably be prime properties).

¹⁹ Source: Investment Property Databank, 2005.

Bailey et al [1963] – i.e. BMN from this point onwards – apply this methodology (screening out all properties that changed substantially due to additions or modifications from the sample) as a procedure to develop real estate indices for the first time. Since then, the literature on both commercial and residential indices has developed quite extensively. Mark and Goldberg [1984] compare other ten types of property index construction methodologies with the results obtained through a BMN estimation.

Palmquist [1980] includes the effect of depreciation in Bailey et al.'s model with a semi-logarithmic equation showing age variable coefficients as estimates of geometric rates of depreciation (i.e. it develops a similar idea to a generalized least squares regression, where properties with large sales intervals are weighted less than buildings with small sales intervals). He then adjusts price relatives by using estimated depreciation rates to construct a “depreciation-corrected price index”. Palmquist finds the new index to be statistically equivalent to a hedonic index carefully derived from a very large and deep database (4,785 sold properties with 21 characteristics each).

Case and Shiller [1987] apply a three-stage weighted repeated-sales methodology (with weights inversely related to the length of time between the two sales) based on the assumption that the variance of error terms across properties may vary (Bailey et al. assumed constant variance). The three steps involved are as follows:

- 1) Weighted OLS estimation of the equation $P_{it} = C_t + H_{it} + N_{it}$, where P_{it} is the log-price of the house i at time t , C_t represents the overall market log-price at time t , H_{it} is a random walk with zero mean (i.e. it allows for drifts), and N_{it} is a random error with zero mean;

- 2) Regression of the squared error terms on a constant (i.e. estimate of the variance of N_{it}) and the time between the two transactions (i.e. estimate of the variance of H_{it});
- 3) GLS estimation of the first equation after having divided each observation by the square root of the fitted value obtained in step two.

This methodology is then applied to create a residential index for four main cities: Atlanta, Chicago, Dallas and San Francisco. Results are compared with the National Association of Realtors data.

Shiller [1991] extends the variety of RSR indices to arithmetic rather than geometric ones. He also shows the methodology to be used in order to distinguish between equal and value-weighted indices. Finally, he gives reasons for preferring this index to a hybrid one that includes quality changes throughout time.

Goetzmann [1992] employs simulation techniques to control for accuracy of different RSR estimators. He finds that the GLS method is the maximum likelihood estimator, and that Bayesian approaches improve accuracy.

When constructing an index based on repeated sales, two separate components in capital growth rates can be detected: fixed portion and stochastic component. Goetzmann and Spiegel [1995] develop two models to control for the fixed component as RSR indices tend to be biased due to capital expenditures leading to improvements and price risk. They apply a maximum likelihood estimation and a three-stage weighted repeat sales procedure by introducing an intercept term, which represents the fixed effect. The two models yield similar estimates; however the ML procedure shows lower standard errors.

Dombrow et al. [1997] examine the underlying assumptions of a repeated-sales model and provide an empirical test for both included and omitted variables as sources of aggregation bias. Their results indicate that virtually all price indices may be biased, the degree of bias being dependent upon the number of variables examined and the instability of their parameters over time.

Gatzlaff and Haurin [1997] analyse the problem linked with variation in property qualities throughout different localities when applying RSR estimations. Using data from a county in Florida, they show that the overall index is biased as opposed to the ones referring to each single locality. This bias is also found to be highly correlated with economic cycles.

Goodman and Thibodeau [1997] study heteroskedasticity and its linkage with two factors: the dwelling age and the length of time needed to resell the property. They find that both these variables are significant in explaining heteroskedasticity in RSR indices. They finally propose a model to correct for this problem and to obtain robust estimates and higher efficiency.

Gatzlaff and Geltner [1998] apply RSR estimation for the first time to commercial property and find that performances of institutional properties (i.e. NCREIF) and of the overall market do not differ too much. They surprisingly discover that such an index conveys little more volatility than an appraisal-based index. However, it also shows movements that a valuation-based measure is not able to capture. At the same time, it leads the NCREIF index.

McMillen and Dombrow [2001] employ a flexible Fourier approach by including a time trend in prices within the estimation equation. They then save degrees of freedom and can subsequently obtain estimates of price movements that are efficient even for periods with few transactions.

Goetzmann and Peng [2002] analyse cross-sectional heteroskedasticity in RSR estimation methods, showing the trade-off between biases in the average return estimate for each period (increased) and the surrounding periods (reduced). Being RSR estimators geometric averages of individual asset returns due to the logarithmic transformation of price relatives, they show that the effect of the cross-sectional variance of asset returns on both the bias in the average return estimate for each period (negative) and the one for the surrounding periods (positive) is significant. In order to adjust the model, they propose an unbiased ML to the RSR that directly estimates index returns (i.e. MLRSR). The estimators represent arithmetic averages of individual asset returns and simulations confirm that they are consistent with time-varying cross-sectional variance.

2.3.3 Hybrid models

Not only repeated-sales regressions and hedonic models are used to produce real estate price indices, but in the literature a combination of the two has also been suggested.

Case and Quigley [1991] jointly apply RSR and hedonic methodologies to produce an index from a database of properties, which is possibly larger than the one used by

previous studies applying only a RSR approach. All these analyses in fact tend to eliminate properties never sold or sold only once and whose characteristics have been changed. Consequently the sample is reduced by more than 90% of the total number of transaction in many cases. Case and Quigley then demonstrate that their model conveys both theoretical and practical advantages (e.g. narrower confidence interval bands) and should then be preferred to pure RSR models when inferring the pattern of market prices of unsold properties.

Clapp and Giaccotto [1992] base their idea on hedonic modelling and develop a framework that uses valuation as the only explanatory variable (in this case “*tax assessor valuation*”). A real estate index is then computed from assessed values and results are compared with RSR methodologies. The two measures tend to reflect the same behaviour within the seven year sample period (1982-1988), and the assessed value index is more efficient (i.e. it uses less data) than RSR ones even if the repeated-sales sample increases. Finally, Clapp and Giaccotto develop a hybrid index from the two methodologies and find a gain in efficiency between 10% and 20%. Few years later, Judd and Winkler [1999] simply apply the assessed value model developed by Clapp and Giaccotto to create a commercial property price index.

Eichholtz [1996] develops a long-run residential index based on a RSR methodology that is corrected through dummy variables to consider changes in the use of the building over time (i.e. this is definitely necessary because of the length of the created index: 1628-1973). The regression equation is: $y = x\gamma + z\lambda + \varepsilon$, where y is the difference of log-prices, x represents a matrix of dummy variables indicating the frequency of

transactions and z is a matrix of dummy variables to consider changes in use. He applies the same procedure to correct for heteroskedasticity as in Case and Shiller, and finds an average price increase of 3.2% p.a. after mid 1940s, while the index level has only doubled in real terms since 1628.

Clapp and Giaccotto [1998] derive a mathematical relationship between coefficients of hedonic and repeat-sales models and show how qualitative characteristic should be chosen to construct a hedonic index. Empirical results also verify theoretical findings. Finally, they prove that the use of assessed value as the only qualitative feature in hedonic models allows parsimonious estimates.

Peng [2002] proposes a combination of a RSR and hedonic modelling based on a GMM regression to obtain estimators that are arithmetic rather than geometric averages of individual asset returns. He proves that the GMM method is more accurate, avoids temporal aggregation and is also flexible (e.g. it allows to compute either equal or value-weighted indices and to include hedonic characteristics). Empirically he uses this method to estimate a commercial real estate index.

2.3.4 Regression techniques and valuations

Another group of interesting applications of the RSR methodology is worth mentioning. These applications constitute the base used to develop a Dutch historical index and a modified version of it will be employed as one of the four methodologies to construct

real estate indices with individual property data in markets with thin information (see chapter 5).

Instead of using two transaction prices at different points in time, in order to obtain a larger number of properties in the sample, Fisher [2000] employs data on both sold properties (last sale price) and appraisals (first valuation when properties entered the NCREIF database for the first time) to create two types of index: equal and value-weighted. The methodology also considers interim cash flows to compute a periodic performance which is less influenced by the valuation impact. The Repeat Sales Index (i.e. RSI) tends to lead the NCREIF Property Index (i.e. NPI from this point onwards) by at least one quarter and does not show any impact of appraisal smoothing. It finally looks similar to an index based on REITs performances.

Geltner and Goetzmann [2000] use a RSR approach with interim cash flows, but they apply it to valuations rather than prices (repeated-measures regression, i.e. RMR). The problem of stale appraisal is then addressed by only using properly done valuations at each measurement point in time. However, the index is still subject to smoothing due to temporal aggregation and possible non-random valuation errors (i.e. it lags behind the NAREIT²⁰ Index by about three quarters). Geltner and Goetzmann conclude that the RMR index leads the valuation-based index by up to four quarters, conveys a slightly higher volatility and does not show a strong seasonal pattern, representing movements that the NCREIF index does not point out. They finally use this method to compute the

²⁰ National Association of Real Estate Investment Trusts. It represents the association of US Real Estate Investment Trusts (i.e. REITs) and it provides indices measuring the performance of this type of vehicles.

appraisal standard error at an individual property level, which is found to range between 6.5% and 14.5%, with an average value around 10%.

Fisher and Geltner [2000] combine a RMR model for capital growth only with a first-order autoregressive filter in order to adjust performances for both stale appraisal and temporal aggregation at the same time. They call the obtained index “Transaction Value Index” and find that it is a better representation of market returns picking up the downturn happened in late 1998 (this is the only valuation-based index showing a negative return).

Following this stream of literature, van Riel and Hordijk [2002] use RMR techniques to produce a Dutch historical index for commercial properties in order to lengthen the ROZ/IPD series that starts in 1995. They employ initial acquisition prices and regress them on last appraised values on a sample of properties composed by the property portfolios of eight major real estate investors, with a total amount of 487 properties transacted between 1981 and 1994. They apply the same procedure Geltner and Goetzmann suggested, but due to a lack of data availability, they recur to mass appraisal using created capital appreciations in order to compute an income and total return. They obtain a plausible time series which however highlights the presence of some issues: the comparability between valuations and prices, the small number of transactions in early years (subsequent strange index behaviour), and the need to test assumptions on the timing of capital expenditure.

2.3.5 Current transaction-based indices

In the UK two main transaction-based indices using a hedonic modelling approach exist: the Halifax House Price Index and the Nationwide House Price Index. The general approach used for these two indices could be replicated for commercial real estate ones.

Both banks use a hedonic model attempting to capture main driving factors for residential pricing. Moreover, they use information coming from the in-house mortgage portfolio dataset (with Nationwide using regional weights, which are derived from the Office of the Deputy Prime Minister's figures). This characteristic signals a pitfall because they come from bank-specific data, which may be not representative of the entire market (e.g. Nationwide itself acknowledges that its mortgage portfolio is biased towards the south of England with a bias that would be automatically shifted to the index level if in-house weights were used).

Finally, the HM Land Registry produces a monthly residential report based on a transaction-based dataset (i.e. reports of sales to the Land Registry) that is available on a highly disaggregated basis across all areas of the country. It shows the rise in the transaction value of houses across the country (excluding transactions under the "right to buy" law). The HM Land Registry index simply shows the average price of houses sold without any weighting. Thus, if the composition of the sample changes in quality and/or the prices of different types of residential buildings rise at different speeds, the

index would be distorted. Notwithstanding this, the use of highly disaggregated data could allow a re-aggregation to compute a new constant-quality series index.

2.3.5.1 Halifax house price index

An example of hedonic modelling used to construct real estate indices is the Halifax approach (see section 2.3.1), described in Fleming and Nellis [1984]. The data set includes characteristics of houses on which mortgages are agreed – i.e. approved rather than completed – by the Halifax (e.g. purchase price, location, quantitative and qualitative features, etc.). The choice to use agreed mortgages allows the provider to cover cases never proceeding to completion with information that is more up-to-date (i.e. price movements indicator) and time consistent (because of the time lag between approval and completion) than the one achievable with completed mortgages. Furthermore, some data-points are discarded because they exhibit characteristics that would distort the dataset (e.g. council house sales).

The information gained from the Halifax mortgage portfolio (about 13,500 transactions per month) is also used to calculate a range of sub-indices reflecting the performance of regions and different types of houses. Regional indices show a quarterly frequency, whilst national ones are computed monthly.

As far as commercial properties are concerned, the hedonic modelling approach used by Halifax may also have interesting applications in the UK market. However, some problems linked with this approach need to be addressed. If we exclude general issues

regarding hedonic modelling (already discussed in section 2.3.1), a major problem attached to the Halifax methodology in particular derives from the use of weights and data belonging to one bank only. As properties included in the Halifax mortgage portfolio do not necessarily represent the typical housing stock of the whole country, the index may not reflect the increase in the market prices (i.e. sample representativity).

2.3.5.2 Nationwide house price index

The Nationwide index uses a hedonic modelling approach and tracks the value of an average house according with standardised characteristics. The weightings put on all the characteristics are determined from the Nationwide own mortgage portfolio except for the regional weightings, which are derived from the Office of the Deputy Prime Minister (i.e. ODPM)'s figures.

Since the Nationwide index adopts the same methodology we have shown above for the Halifax index (the only difference being hedonic factors built in the model), the Nationwide index construction methodology is not considered here.

2.3.5.3 HM Land Registry house price index

HM Land Registry produces a monthly residential property price report based on transaction data in all areas of the country. The data provided are described in HM Land Registry (2002), updated on www.landreg.gov.uk. The main advantage of the Land

Registry data is that they are available on a highly disaggregated basis across England and Wales.

The data show the rise in the transaction value of houses across the country, based on reports of sales to the Land Registry. From this databank, a capital value index of housing prices is created. As for the Halifax and Nationwide indices, some sales are excluded, where the transaction price is distorted (e.g. those transacted under 'right to buy' legislation). The Land Registry data simply show the average price of houses sold without any weighting. This means that, if the composition of sold houses changes and/or the prices of different types of house are rising at different rates, the index would be distorted. However, because disaggregated indices are produced to show price movements of houses showing different features (i.e. old vs. new properties, or detached vs. semi-detached vs. terraced vs. flat, or by postcode), it would be possible to recreate a weighted index from the Land Registry figures. The weights could be based on ODPM and other government figures for the numbers of different types of property and the ones of properties in each region. Alternatively, a representative base year could be determined and Land Registry figures adjusted so that the average sale price would be based on consistent weights over time.

It is unlikely that an adjusted Land Registry approach would improve upon the data provided by the Halifax and Nationwide, unless there are further problems with those indices of which we are not aware.

However, the sample size of the Land Registry figures might make them attractive if the Halifax or Nationwide coverage were to shrink, even if the Land Registry approach cannot provide more than a 'barometer' of the residential property market.

There are a number of differences between the three forms of housing market indices that could lead to differences in 'performance'. The main differences are as follows:

- potential dissimilarities in seasonal adjustment factors (the Land Registry figures have no seasonal adjustment), which may be important for short-term decision making;
- different weighting systems (Land Registry unweighted, Halifax weighted on the basis of 1983 advances, Nationwide weighted on the basis of ODPM data for regional characteristics and Nationwide advances for other characteristics);
- different statistical methodology.

2.4 SYNTHETIC VALUATION-BASED INDICES

Real estate agents, government-based bodies, or independent associations tend to provide basic information on the property market. They normally show simple measures of market rents and yields that are based on either transactions data or judgmental factors (e.g. questionnaires).

These indices are then used to produce portfolio performance measures, such as total return, capital growth and income return. In order to achieve this goal, data providers make some (occasionally very strong) assumptions, such as income return being equal to the equivalent yield.

The main difference between valuation-based and synthetic valuation-based performances comes from the type of return that each index is trying to measure. The former shows the actual performance of a property investor (the data comes from actual cash flows including both capital expenditures/receipts and rental income net of all non-recoverable operating costs). The second measure, instead, reports market trends considering a hypothetical portfolio continuously re-let at the open market rental value with no vacancy. These assumptions then make the latter lead the former and be preferred for some index uses, such as forecasting which needs most updated information. A second major difference derives from the difference of the type of assets and their location between the two methodologies. Valuation-based indices include all kinds of standing investments, while synthetic valuation-based indices normally refer to prime properties situated in primary locations.

In the UK for example, CB Richard Ellis produces two indices reflecting market rents and equivalent yields at a sector and regional level. These figures are then combined to create a portfolio index (based on valuations) which “pretends” to be in some way comparable to the IPD index. These performance measures are available on an ongoing basis and are often used for forecasting purposes as they represent the “edge of the market”.

The US case is different from the UK one: the obtained index is computed for research purposes and it is not available on an ongoing basis. It is also intended to be transactions-driven because the cap rate employed to produce capital growth rates reflects movements in the actual transaction market, rather than movements in the “appraisal world”.

The next part of the section explains the two methodologies developed in the two markets.

2.4.1 Current synthetic valuation-based indices

2.4.1.1 CB Richard Ellis methodology

CB Richard Ellis (CBRE) provides a Rental Index and an Average Yield. The two quarterly (February, May, August and November) measures indicate respectively the OMRV and the equivalent yield of rack rented properties of a standard specification (i.e. hypothetical properties). Each quarter, CBRE collects rents and yields of notional

properties from its UK valuers (i.e. every quarter each valuer is asked to give the rent and yield of the hypothetical property identified by criteria explained below. Each valuer is responsible for the same property every quarter).

We use two examples to clarify the definition of a hypothetical property.

For “high street shops”, rents and yields are based on Zone A for a unit of:

- 7.6m (frontage) by 24m (depth);
- 46 – 93 sqm storage;
- located in the prime 100% trading pitch of the location;
- let on Full Repairing and Insuring (i.e. FRI) terms.

Secondly, “central London offices” show the following characteristics:

- new or recently refurbished building of grade A;
- 930 sqm in best position;
- let on FRI terms.

This methodology immediately reveals two types of biases: firstly a “company bias” due to the impact of CBRE’s view on the market, and secondly a “valuer bias” due to the fact that the same valuer provides the information about the same property every quarter (i.e. even if this method maintains a consistency throughout intervals, it reflects the specific valuer’s perception of the market cycle).

The overall sample used to construct the index includes 1,129 locations. Properties can be grouped into four main sectors: 555 are shops, 239 offices, 187 industrials and 148 retail warehouses. Regions are defined as for the Government Office (i.e. GOR).

CBRE indices are cap-weighted indices measuring changes in rental values and yields. They are computed through a bottom-up approach, starting from single locations and subsequently building up (through a simple weighted summation) measures for regions, sectors and the overall market. Regional indices are compiled using capital values of hypothetical properties as weights, while IPD regional and sector weights are used to form respectively sector indices and the All Property Index.

CB Richard Ellis also releases a total return index – obtained from capital growth and income return indices – by using the above information and making some strong assumptions regarding both the income and the discount factor:

1. the income is assumed to be equal to the OMRV (i.e. properties are let at the OMRV with a quarterly revision);
2. the rack rented equivalent yield is used as a discount factor to compute the capital value;
3. the income return is assumed to be equal to the rack rented equivalent yield.

The capital growth index at time t (CV_t) is then computed discounting the OMRV at time t ($Rent_t$) by the equivalent yield at time t ($Yield_t$):

$$CV_t = \frac{Rent_t}{Yield_t}$$

giving a quarterly capital growth at time t (cg_t) computed as follows:

$$cg_t = \frac{CV_t}{CV_{t-1}} - 1$$

The capital growth is finally added to the income return (i.e. $Yield_t$) to obtain a total return measure:

$$tr_t = cg_t + Yield_t$$

2.4.1.2 Russell-NCREIF/ACLI methodology

Fisher et al [1994] developed a portfolio index using two main sources of information: Russell-NCREIF database, and the American Council of Life Insurers (i.e. ACLI). The first provider shows the historical Net Operating Income (i.e. NOI) of commercial properties, while the second one reports the cap rates associated with properties for which association members issued commercial mortgages during the measurement period:

$$Cap_t = \frac{NOI_{t+1}}{P_t}$$

where NOI_{t+1} refers to the net operating income at time $t+1$ (i.e. next interval) and P_t is the transaction price at time t . Fisher et al. then divide the Russell-NCREIF NOI by the ACLI cap rate to obtain an estimate of the average transaction price of commercial properties. In order to decrease the temporal aggregation effect, they use an annual frequency and apply the fourth-quarter ACLI cap rate and the following year Russell-NCREIF NOI. The end year value is then obtained from $V_{t,4} = \frac{NOI_{t+1}}{Cap_{t,4}}$, and annual

returns are set to be equal to the first differences of the logs of year-end values. The new index shows a volatility of 9.36% and a first-order autocorrelation coefficient of 0.39. Both figures are much more similar to the features of a “market value index” (see section 2.2.2.2) than to the ones of a smoothed valuation-based index.

Even for the US case, several issues have to be raised:

1. the samples of properties used to produce the index (ACLI properties for cap rate and Russell-NCREIF ones for NOI) are not consistent;
2. time-varying quality and characteristics of the ACLI sample are not allowed (i.e. the "hedonic" issue of transacted properties over time is not considered);
3. several ACLI cap rates may better represent "idealised" or "expected" cap rates rather than actual transaction cap rates for two main reasons: they are based on a “stabilised NOI” rather than on the current one, and their majority refers to refinancing rather than purchases (i.e. the denominator is an appraised value rather than a price).

The first two issues might cause a random artificial volatility (i.e. noise) added to the normal one. The third problem would instead lead to an index that is extremely sensitive to inflation (i.e. high cap rates would be achieved during inflation peaking periods with a subsequent fall in synthetic index levels).

2.5 VEHICLE-BASED INDICES

Vehicle-based indices (e.g. UK property companies, US REITs, etc.) are, for sure, adding new information to other performance measurements in real estate markets. However, this type of indices reflects not only a property performance, but also the impact of other factors.

A vehicle-based index is normally computed as a weighted average of share prices (either property companies or REITs), with weights equal to the number of shares:

$$I_t = K * \frac{\sum_{i=1}^n p_{i,t} * n_{i,t}}{\sum_{i=1}^n p_{i,t-1} * n_{i,t-1}}$$

where:

K = Value of the index at the base date

$p_{i,t}$ = Share price of company (REIT) i at time t

$n_{i,t}$ = Number of shares (quotes) of company (REIT) i at time t

This computation leads to the construction of an index which does not necessarily represent property price movements because it is affected by some other factors, such as company policies, leverage, tax issues, etc. However, a similar problem is also found in valuation-based indices, where true price movements are hidden by smoothing and valuation accuracy.

In the real estate literature many papers analyse the relationship between securitised real estate performances (of both the overall market and each single property company) and unsecuritised indices, stock markets and economic and financial variables in order to identify the underlying “pure” property component. Main techniques used to assess the linkage between public and private real estate performances vary significantly:

- correlation coefficient to test for contemporaneous relationship;
- granger causality tests to test for intertemporal linkages;
- a combination of ARIMA or VARMA models and cross-correlation coefficients;
- cointegration to test for an existing long-run relationship;
- spectral analysis to test for cyclical patterns.

2.5.1 Factors driving the performance

If vehicle-based performances are used to retrieve returns of direct investment in real estate, several factors, which may differentiate these two types of measures, need to be considered.

The return of investments in property companies or REITs should (at least in the long-run) reflect a property-related performance, because share prices incorporate fundamental values. However, these measures show returns of geared companies, with the level of gearing increasing the risk associated to this type of investment, as well as causing the return on the equity capital to deviate from the return on the underlying assets of the company. Differently, valuation-based indices do not represent levered

returns in either the UK or US markets: the IPD index does not include any geared component in its measurements, while the NCREIF index includes levered properties, but only after adjusting their performance to show an ungeared return.

Moreover, the liquidity in equity and real estate markets is very different and this feature should be priced in the two indices accordingly. If we want to sell a property, it will probably take us few months, and a willing buyer needs to be found. Instead equities have a common market place and, notwithstanding price constraints due to demand and supply levels, it is always possible to buy or sell specific shares on an instant basis. The heterogeneity feature of the real estate market also sharpens this liquidity issue.

Furthermore, the balance sheet identity of a company states that total assets should equal the sum of equity and debt. Hence, cash flows from total assets should equal cash flows from equity and debt. One of the main components of generated cash flows is taxation, which tends to be different for equity, debt and direct real estate investments. So far, for simplicity, no model included taxation differentials in the literature. We also decided to follow the same approach.

Finally, real estate share prices probably incorporate an equity effect that we would expect to be greater the higher the frequency of computed returns. However, the equity effect may also be reflected in private real estate indices as equity and property markets are not perfectly independent and we may expect to see some linkages between them.

2.5.2 Models to retrieve direct real estate performances

The real estate literature has tried to deal with these issues and adjust vehicle-based performances in order to obtain an index representing direct property returns. This section analyses several models used to retrieve useful direct property information from vehicle-based indices. The literature is divided into four main groups depending upon the measure with which real estate vehicle-based indices are compared.

2.5.2.1 Relationship between direct and indirect investment in real estate

Giliberto [1990] studies the relationship between equity REITs (i.e. EREITs) and direct real estate by regressing financial assets (equities and bonds) returns and a seasonal effect on both indices. The correlation coefficient between the two residuals is found equal to 0.44 (significant at 99% level), suggesting that after removing the effect of other financial assets, the two series show a common factor (i.e. “pure” property factor), which is persistent in the lead-lag structure too (i.e. one to four quarters lagged EREIT residuals are correlated with valuation-based ones and their coefficient is respectively equal to 0.32, 0.45, 0.43 and 0.32).

Gyourko and Keim [1992] relate real estate stock portfolios – constructed from company data – to commercial valuation-based indices and other financial assets. For quarterly frequencies they find an autoregressive process in which EREITs (with both

no lags and one quarter lag), residential markets, small stocks and bonds are significant in explaining Russell-NCREIF performances.

Myer and Webb [1993] analyse time series properties of equity REITs along with common stocks, closed-end funds and valuation-based property indices, by looking at both risk / return characteristics and skewness and kurtosis. They finally assess the intertemporal relationship between these indices via a granger causality test. They find that the behaviour of EREITs is more similar to the one common stocks and funds show, with EREITs “granger-causing” valuation-based indices (i.e. this is due to the slow process of information “acquisition” in unsecuritised real estate markets).

Myer and Webb [1994] also study the relationship between REITs, stocks and direct real estate limiting their analysis to the retail sector between 1983 and 1991. They find same evidences as in the previous paper with a significant relationship between stocks and REITs. This would suggest the existence of some common factors (e.g. average rents) in addition to market performances. However, the lack of a dependency between private real estate and either REITs or stocks reduces the explanatory power of these common factors (their existence becomes more doubtful).

Furthermore, the relationship between securitised and unsecuritised property performance is analysed by Moss and Schneider [1996], who compare cash flows of valuation-based indices with the ones of vehicle-based indices, and the NCREIF yield index with the equity REITs share price index. They use both ARIMA and VARMA models to test whether EREIT returns reflect real estate performances. With the ARIMA model, they find no significant correlation between the residuals of the two

cash flow series at lag 0, but significant correlation coefficients at lag 1, 4 and -3 (i.e. the lead-lag structure is not clear because there are both positive and negative lags being significant). The VARMA model strengthens these results and finds that the EREIT cash flows index leads the NCREIF by one quarter (i.e. if a deviation from the univariate process happens in the first index, this will happen in the same direction in the second one after one quarter). They also find only spurious correlations between NCREIF yield rates and EREIT prices and thus conclude that the valuation process in the two markets – direct and indirect – is different. This can be “partially attributable to the EREIT use of leverage” and to different investors’ characteristics.

Liang et al. [1996] raise a similar issue limiting their analysis to residential indices. A “double-hedged” apartment REIT index is computed by stripping out the impact of the stock market and REITs on its performance (through a simple multifactor model). This return measure satisfactorily tracks the performance of the Russell-NCREIF and also shows better time series properties (i.e. the hedged index reflects neither smoothing, nor seasonality). Moreover, when this measure is used as a proxy for portfolio allocation choices, apartment real estate tend to be included in mixed-asset portfolios.

Seck [1996] applies non-structural procedures (e.g. variance ratio tests and variance decompositions of VARs) and finds a low degree of substitutability between direct and indirect investments in property. The former is based on appraisal data, while the latter seems to reflect transaction prices (i.e. only valuation-based returns follow a random walk). Finally, Seck finds that direct property markets and vehicle-based indices are

more predictable by using respectively industrial production, and the combination of stock markets and the term structure of interest rates.

Barkham and Geltner [1995] transform direct and indirect real estate performance to make them comparable by unsmoothing valuation-based indices²¹ and de-gearing REIT and property company share prices. They find that – for both the UK and the USA – price discovery of the common commercial property value factor occurs first in the securitised market and then it is transferred to the private market only after at least a year, with the UK showing a faster transmission process.

Lee et al. [2000] analyse time-series properties of several UK real estate indices and compute correlation coefficients and granger causality tests. They reach the same results previously obtained (i.e. low correlation between private and public real estate markets, with indirect property leading direct investments and being highly correlated with stock markets), but they add new information by suggesting the same findings for all possible frequencies (i.e. annual, quarterly and monthly).

Brown and Liow [2001] use spectral analysis to shed light upon the cyclical relationship between unsecuritised and securitised markets. They find an existing common cyclical path showing a full cycle which is eight years long. So, even if in the short run, property stock prices tend to lead direct real estate of up to one/three quarters, the long run relationship signals the presence of co-movements in the two markets. However, Brown and Liow's result is weak because they find co-movements just in one of the peaks of the cycle (after 31.3 quarters = approximately 3.5 years).

²¹ See Section 2.2.2 for a discussion on valuation smoothing.

2.5.2.2 Stock market effect

Sagalyn [1990] uses a CAPM framework to study the relationship between securitised (i.e. REITs and Real Estate Companies or RECs) and capital markets (i.e. equities). She also analyses the change in the linkage during different business cycles – upswings and downswings. A report on ex-post performances of survivor real estate securities shows, in periods of high growth, a lower volatility (and lower systematic risk) and a higher average return relative to the overall stock market. This paper also finds that real estate systematic risk is underestimated in periods of low economic growth when it is measured through valuation-based indices. This feature can be partially explained by smoothing, but it needs further investigations. Secondly, the comparison between REITs and RECs suggests that an active property management is not rewarded and different types of securities lead to different results. Finally, REITs (but not RECs) tend to produce an excess performance and RECs returns also underpin development and construction cycles, and not only standing investment ones. These last two findings may be explained by a different portfolio composition between the two types of real estate vehicles.

Ling and Naranjo [1999] analyse the relationship of both unsecuritised and securitised property markets with stock markets through multifactor asset pricing models. They find only vehicle-based indices are integrated with stock markets (i.e. showing the same systematic risk premium), with a degree of integration rising during 1990s. Two methods are used: a non-linear seemingly unrelated regressions (i.e. SURE) model and

one allowing for time-varying coefficients. The second model is also useful to control for fixed coefficients robustness and to test for changes in market integration over time.

2.5.2.3 Analysis on single property companies

Newell and Chau [1996] study the relationship between direct and indirect investment in real estate in Hong Kong. They compute correlation coefficients, serial correlations and granger causality tests to assess time series properties and the linkage between each property company (major blue-chip property developers and investors) and the direct market. The main finding suggests that Hong Kong property company returns contain transaction-based information (this is mostly true for investment companies) that is incorporated in unsecuritised markets only after one quarter.

Newell et al. [1997] compare the performance of property company shares with direct real estate returns. They discover that property companies provide useful information about real estate transaction prices, even if they show high correlation with the stock market and low correlation with the direct property one. Some property companies incorporate a “pure” property factor more strongly than others and granger-cause direct property performances by two to three quarters. Finally, they find that stripping out the stock market distortion does not determine a stronger common property factor between the two markets. For asset allocation purposes, this results implies the opportunity property vehicles represent in terms of both diversification and liquidity within a portfolio already including private real estate.

Stevenson [2001] extracts both the gearing effect – Geltner and Barkham’s method – and the general equity market impact – simple single index model – in order to identify style attributes of several UK property companies. He finds no improvements in the correlation coefficient between property companies and the IPD index when de-gearing techniques are applied. However, results show an impact on five-years rolling correlations between property companies and equity markets (i.e. the de-gearred series shows a correlation coefficient that is not significantly different from zero, while the original series reports a figure ranging from 0.6 to 0.8).

2.5.2.4 Economic and financial variables

Chau et al. [2001] apply an APT model to four sectors of the Hong Kong property market, by considering three types of variables (i.e. capital markets, local securitised property factors and local economic and property market variables). They reach two main results: securitised real estate returns do not contain much information about direct real estate markets when the impact of both global and local capital markets is stripped out; local economic and property market information shows high significance and explanatory power when unsmoothed direct property returns are modelled. This is tested through two main procedures: simple correlation coefficients and an increasing predictive power of multi-factor equations including these variables.

2.6 Index construction methodologies and markets with thin information

So far we have presented several index construction methodologies adopted in real estate markets. We also critically identified the main issues which are associated with each type of performance measure and may cause differences between index returns (e.g. smoothing for valuation-based returns, gearing for vehicle-based returns, survivorship bias for repeated-measures regression).

Some methodologies (e.g. standard valuation-based indices) require a great amount of data. They can only be used in markets with good information flows and their data collection process is very expensive and time consuming. Moreover, in markets with thin information, some pieces of information needed for these methodologies (e.g. periodical valuations) are not available. Therefore, in such markets, other methodologies (e.g. adjusted vehicle-based performances) using very little information are more appropriate to construct a proxy for direct real estate returns.

The distinction between index construction methodologies using either a large or a small amount of data is most relevant when we intend to create historical performances. In this context, in fact, the availability of information becomes a significant issue and it sometimes drives the application of standard index construction methodologies to data

which are easily accessible²². As an example to clarify this point we can consider the use of acquisition price and most recent valuation, instead of two successive sale prices in standard repeated-sales regression models to obtain repeated-measures regression indices.

In the following chapters, we develop three main index construction methodologies which can be used to create a proxy for direct real estate returns in markets with thin information. First, we develop data sets which are necessary to construct these indices in markets with good information flows. We then compute historical return series in these markets. Finally, we compare the new indices constructed using the three proposed methodologies with original and unsmoothed valuation-based returns (i.e. IPD index) to determine the efficacy of different approaches to represent direct real estate returns in markets with thin information.

²² E.g. In our repeated-measures regression models we suggest to use, for each individual property, the acquisition price and the most recent valuation, instead of two successive sale prices.

Chapter 3

FROM SECURITISED TO UNSECURITISED REAL ESTATE RETURNS: WACC AND SMOOTHING

3.1 INTRODUCTION²³

Direct investment in real estate indicates the ownership of buildings for the purpose of making a profit deriving from two main sources: income (received rent minus costs) and capital growth (increase in capital value, net of capital expenditures). Indirect investment in real estate is defined as the ownership of a stake in a vehicle that owns and manages a portfolio of properties on behalf of its shareholders.

The advantage of this second type of investment relies on the higher liquidity offered for exit strategies. For example, if the investor wants to sell his/her stake in a real estate vehicle, he/she can either sell it in the market (if the vehicle is traded) or exercise the right to sell it (by following the exit strategy set out in the investment prospectus, and eventually paying an exit fee). On the other hand, if an investor wants to sell his/her office building (or shopping centre), he/she will have to face an illiquidity issue: will he/she be able to sell the property at a fair value and within a reasonable amount of time (normally not less than two or three months in the US and UK markets)?

Moreover, portfolio managers want to diversify their investments and real estate is an asset class offering a low correlation with both equities and bonds and a return/risk profile that stays between the two. However, even if real estate vehicles are “accepted” as “substitutes” for direct investments in real estate, their time series properties suggest

²³ The main body of this chapter was published in the *Journal of Property Investment and Finance* and was awarded the “Gerald Brown Prize” as the best paper presented in Real Estate Investment and Valuation at the 2002 European Real Estate Society conference – see Booth and Marcato [2004b].

these vehicles show performances behaving more similarly to equities than to direct properties.

Finance theory studied the information transmission and diffusion effect between these two markets by suggesting that information is firstly incorporated in real estate vehicles and subsequently transmitted into direct property returns. This is an intuitive result for two main reasons. We expect fundamental values to be reflected into share prices, at least in the long-run, and secondly indirect real estate performances are computed with share prices, whilst direct real estate returns are based on valuations since buildings are heterogeneous and indivisible, and their transactions are not frequent enough. In other words, we would expect real estate vehicles (also known as public or securitised or indirect real estate markets) being correlated with underlying performances of their assets (direct property, also known as private or unsecuritised real estate).

As discussed in section 2.5, different models (sometimes even jointly) have been used to assess the existing different return and risk characteristics of valuation-based and vehicle-based indices: style analysis (eg. Stevenson [2001]), equilibrium of asset classes (e.g. Giliberto [1990], Gyourko and Keim [1992], Myer and Webb [1993, 1994]), both global and local economic and financial factors (e.g. Chau et al. [2001]), time series properties such as smoothing, and other factors such as leverage (eg. Barkham and Geltner [1995]). The linkage between different performance measures has also been measured by significantly different techniques: simple correlation coefficients and granger causality tests for respectively contemporaneous and intertemporal relationships

(e.g. Newell and Chau [1996], Newell et al. [1997], Lee et al. [2000]), a combination of ARIMA or VARMA models and cross-correlation coefficients (e.g. Moss and Schneider [1996]), cointegration and spectral analysis (e.g. Ling and Naranjo [1999], Brown and Liow [2001]) to test for respectively long-run relationships and cyclical patterns.

However, the issue of price discovery in real estate markets is still far from being fully understood. If we assume a semi-strong market efficiency, real estate stock prices should fully reflect direct property prices. The factors differentiating securitised and unsecuritised real estate performances are then smoothing (i.e. a high level of serial correlation caused by index construction methodologies) for direct property markets and the amount of leverage for indirect ones – since private real estate returns are unlevered²⁴. In the literature we can find several unsmoothing procedures (e.g. Quan and Quigley [1991], Geltner [1989, 1993a and 1993b], Fisher et al [1994], Chaplin [1997], Brown and Matysiak [1998], Wang [1998], Geltner and Goetzmann [1999], Cho et al [2001]) that are developed starting from different assumptions (e.g. efficient vs. non-efficient markets, constant vs. time-varying serial correlation, etc.). A few papers also try to address the leverage issue (e.g. Barkham and Geltner [1995], Stevenson [2001], Saunders and Ward [1978]) by creating unlevered measures of performance with either a weighted average cost of capital or capital asset pricing model.

²⁴ Additionally, we also acknowledge that the taxation systems of equity, debt and direct investment in real estate are different, but we assume them being equal in our model.

In this chapter we apply several methods to unsmooth property indices to demonstrate that results on the dependency between adjusted direct and indirect performances do not significantly vary if different unsmoothing techniques are used. We then apply a model to adjust vehicle-based indices for the gearing effect.

When comparing actual and adjusted figures, we assume market efficiency (at least in a weak form) in the long run as we expect properly adjusted returns of real estate vehicles and direct property to match as equity prices are driven by fundamentals. However, in the short run we may expect a different investor behaviour which affects the features of vehicle-based performances (i.e. noise due to speculative trading). So by using an annual frequency (investor with a long-run investment horizon), we would expect adjustments to improve the dependency between the two series and the similarity of their return to risk profiles (i.e. adjusted vehicle-based and valuation-based indices should respectively show a lower and higher standard deviation than the one computed from original indices), and to eliminate an existing intertemporal causality. If, by passing from an annual to a monthly frequency this result is no more valid, there could be two plausible explanations. Firstly, performances of vehicles are reflecting a different investment horizon and a higher equity effect (e.g. investors may decide to buy shares of real estate vehicles for speculative reasons linked to new information to be released). However, we would expect at least a small improvement of the dependency between the two adjusted indices. If this does not happen, we may also conclude that there may be useful information embedded in vehicle-based indices that is complementary to the one entrenched in valuation-based returns.

If we manage to establish a relationship between securitised and unsecuritised real estate returns in markets which show these two types of performance measures, we can therefore use vehicle-based indices to investigate the behaviour of property markets with thin information. In such markets (e.g. Italy, Spain, Portugal, etc.), in fact, it is common to find property vehicles quoted in the stock exchange. Their data may thus be adjusted with a WACC model to pass from indirect to direct real estate performances.

3.2 METHODOLOGY AND DATA

The indices chosen for both annual and monthly investigations respectively are:

- Annual returns from the IPD annual index and the Datastream Real Estate Sector index from 1970 to 2004.
- Monthly returns from the IPD monthly index and the FTSE 350 Real Estate Sector index from January 1995 to December 2004.

The IPD Monthly index includes only properties with a fee-based monthly valuation and covers 3,200 buildings worth more than £ 28 billion at the end of 2004. This represent almost 25% of the IPD annual index sample (which is more or less 45% of the whole direct real estate market). Hence the monthly database shows at least 10% market coverage.

The gearing ratio for the annual analysis is directly obtained from Datastream, the main rationale being the consistency of the dataset. The gearing ratio for the monthly study is

computed from original sources, using published accounting information and market equity values of companies composing the FTSE 350 Real Estate Sector. The rationale for this choice is the lack of a monthly series of gearing ratios for Datastream indices and the choice to reflect market values rather than book values. In fact, Datastream normally computes the average gearing ratio of an index by using, for each constituent, annual accounting figures of both debt and equity. Consequently, to use a monthly frequency, we should interpolate the Datastream gearing ratio index throughout the year and still obtain figures based on book values. Instead, if we compute a gearing ratio from primary sources, we can account for debt issues during the year and can incorporate the market value of the equity component.

The use of the short sample period for the monthly frequency (i.e. the IPD monthly index starts in 1987, but we only start from January 1995) is due to the availability of data which are necessary to compute the leverage ratio from primary sources.

3.2.1 The WACC model

When we analyse and compare performances of securitised and unsecuritised markets, we need to consider all plausible causes leading to a different behaviour.

Vehicle-based indices reflect the impact of a portfolio of geared properties. We would expect this portfolio to show a higher volatility than the one composed by de-geared properties. In order to eliminate the effect of leverage, we use the same model Barkham

and Geltner [1995] and Stevenson [2001] used. We consider a weighted average cost of capital (i.e. WACC) framework, starting from the following balance sheet identity:

$$P_t + A_t = E_t + D_t$$

where P_t represents property assets held at time t , A_t other assets held at time t (i.e. short term assets), D_t liabilities (i.e. debt) at time t , and E_t shows shareholders equity at time t .

From this identity a return relationship follows:

$$r_{pt} * \frac{P_t}{E_t + D_t} + r_{at} * \frac{A_t}{E_t + D_t} = r_{et} * \frac{E_t}{E_t + D_t} + r_{dt} * \frac{D_t}{E_t + D_t}$$

where r_{it} indicates the return of the asset/liability i at time t .

Therefore, by assuming $r_{at} = r_{dt}$ and rearranging the equation (see the Appendix for full derivation), an approximation for unlevered property returns is obtained from vehicle-based returns (i.e. property companies or REITs indices) as follows:

$$r_{pt} = \frac{r_{et} - \left(1 - \frac{P_t}{E_t}\right) * r_{dt}}{\frac{P_t}{E_t}} \quad (3.1)$$

The difference with both Geltner-Barkham and Stevenson's models is in its application. For the first time, we also apply this model to a monthly frequency. In this part of our analysis we also use market values rather than book values to create a monthly gearing ratio from primary sources.

Since there is no published information with a monthly frequency that allows us to derive an average gearing ratio for the FTSE 350 Real Estate Sector Index directly, we compute the gearing ratio by examining the individual constituents of the monthly index and their debt issues on a monthly basis. The average gearing ratio of the indirect property index for each month is then computed by taking the weighted average gearing ratio of the constituents at the beginning of the same month (where the weights are market values of companies).

The leverage ratio for company i at time t (i.e. L_{it}) is given by $L_{it} = \frac{D_{it}}{MV_{it}}$, where D_{it} and MV_{it} are respectively company i 's debt and market value at time t . The leverage ratio for the index is then computed with a simple weighted average of company ratios, with weights equal to the market value of each company.

For simplicity, we assume that repayments of debt only occur at the end of the year, leaving only new issues as a variable in the numerator (debt) each month. This assumption is made necessary by the limitations of the publicly available data. We use disaggregated company-level monthly data to determine the gearing ratios and debt issues. The new issues are assumed to take place at the beginning of each month.

Monthly market values for each property company are obtained through a secondary source (Datastream), while the value of the debt is collected from primary sources through company balance sheets, which indicate the date and amount of new debt issued during the year.

It should be noted that, apart from the issue of the timing of debt issues, which represents a simplifying assumption, off balance sheet leverage is not included in our analysis. There may be other accounting issues too that, when resolved, would enable a more precise de-gearred real estate share index to be developed. These issues may be addressed in further research.

3.2.2 Unsmoothing valuation-based indices

When an index and not an individual property is concerned, three main factors may cause smoothing: the index construction in itself (i.e. temporal aggregation of individual appraisals referring to different dates), valuations not done at each measurement interval (i.e. stale appraisal), and “minimum adjusting variations” (i.e. a minimum level of capital appreciation/depreciation to induce a valuer to change the appraisal figure).

If we analyse time-series properties of valuation-based indices we then find a high autocorrelation that may indicate real estate returns as a long-memory process. However, this feature is significant and reduces the volatility so much so that it is difficult to compare return/risk characteristics of different asset classes in an asset

allocation framework²⁵. In this section we apply four main unsmoothing procedures in order to reduce the smoothedness of real estate indices. We also carry out a sensitivity analysis on the unsmoothing parameter in order to demonstrate that results are not dependent on the level of parameter used in the estimation. We apply these techniques to both nominal and real (adjusted for inflation) returns. We also compute dependency measures for both capital growth and total return indices. As results do not significantly differ, only the ones obtained with nominal total returns are shown and commented in this section.

3.2.2.1 Unsmoothing procedures

Several unsmoothing techniques have been suggested in the literature. Here we apply four main procedures: first and n^{th} autoregressive filter (Geltner [1993], FGW [1994]), volatility weight (FGW [1994]), and market growth states (Chaplin [1997]). We have decided to refer only to procedures using real estate time series properties, as opposed to methods relying on indirect linkages with other variables (i.e. Wang [1998]). We also decided not to apply the Brown and Matysiak [1998] technique because a time-varying parameter cannot be applied to an annual series (not enough observations are available). Finally, we have not tested the Cho et al. [2003] methodology because specifications

²⁵ E.g. According to a mean-variance portfolio theory, the return/risk profile of direct investment in real estate does not normally justify current property weights in institutional investors' portfolios. A much higher weight would be expected because of the low risk / high return profile valuation-based indices show.

included in their model are redundant (i.e. they apply an autoregressive procedure by using differences in returns rather than returns).

First order autoregressive filter (i.e. foarf)

The first unsmoothing procedure is the one suggested by Fisher-Geltner-Webb [1994], i.e. first-order autoregressive reverse filter. Unsmoothed capital growth rates for direct real estate investment (i.e. ucg_t) are computed as follows:

$$ucg_t = \frac{[cg_t - \alpha_1 * cg_{t-1}]}{(1 - \alpha_1)}$$

where cg_t is the capital growth of the valuation-based index at time t and α_1 is the first order autoregressive parameter of the same series.

An income return recalibrated for the unsmoothed capital value index (i.e. uir_t) is computed as follows:

$$uir_t = \frac{inc_t}{ucgi_t}$$

where inc_t is the income return at time t and $ucgi_t$ represents the unsmoothed capital growth index at time t .

The adjusted direct real estate return at time t ($udre_t$) is finally derived as the sum (at time t) of the two components: the unsmoothed capital growth and the unsmoothed income return:

$$udre_t = ucg_t + uir_t$$

Three main assumptions are implied in this model: firstly the values of the mean for the adjusted and unadjusted series are equal; secondly, the model holds over time (i.e. stationarity); finally, purely random errors are left out of the index (i.e. there is no noise).

Nth order autoregressive filter (i.e. noarf)

If we consider an autoregressive process with more than one lag, we can obtain a more generalised model to unsmooth direct property indices. However, there is no strong theoretical a-priori suggesting the existence of a relationship between annual capital growth rates and their lagged figures when more than two lags is considered (e.g. comparables used to value a property may be taken from last year transactions, but it would be very difficult they are taken from transactions completed two or more years ago). Thus we apply a second order autoregressive filter to annual returns and we use up to twelve lags to model monthly returns since we think values incorporate information referring to a few months before. The generalised formula to retrieve the unsmoothed capital growth is as follows:

$$ucg_t = \frac{cg_t - \alpha_1 * cg_{t-1} - \alpha_2 * cg_{t-2} - \dots - \alpha_n * cg_{t-n}}{(1 - \alpha_1 - \alpha_2 - \dots - \alpha_n)}$$

We find the 1st, 2nd, 4th, 6th and 12th lags to be significant, so we restrict our model to the following form:

$$ucg_t = \frac{cg_t - \alpha_1 * cg_{t-1} - \alpha_2 * cg_{t-2} - \alpha_4 * cg_{t-4} - \alpha_6 * cg_{t-6} - \alpha_{12} * cg_{t-12}}{(1 - \alpha_1 - \alpha_2 - \alpha_4 - \alpha_6 - \alpha_{12})}$$

The previous methodology is used to obtain unsmoothed income returns $\left(uir_t = \frac{inc_t}{ucgi_t} \right)$

and unsmoothed total returns ($udre_t = ucg_t + uir_t$).

Volatility weight (i.e. fivi)

We use the same methodology applied by Fisher, Geltner and Webb [1994] with a first order autoregressive process. Residuals are computed from $(cg_t - \alpha_1 * cg_{t-1})$, and their

volatility is used to compute the weight $\left(w_0 = \frac{2 * \sigma_{resid}}{\sigma_{equity}} \right)$ that is necessary to obtain the

unsmoothed capital appreciation rate from the following equation:

$$ucg_t = \frac{(cg_t - \alpha_1 * cg_{t-1})}{w_0}$$

The previous methodology is used to obtain unsmoothed income returns $\left(uir_t = \frac{inc_t}{ucgi_t} \right)$

and unsmoothed total returns ($udre_t = ucg_t + uir_t$).

Market growth states (i.e. states)

If we consider different moments during the market cycle, we would probably find that the unsmoothing parameter changes. As in Chaplin [1997] model, we assume that this unsmoothing parameter is higher for falling than for rising markets (i.e. valuers will tend to link their new valuation to the previous one with a greater extent in falling markets). Secondly we assume that the stronger is the appreciation (or depreciation), the

higher the parameter should be (i.e. if a market is falling sharply, valuers will tend to adjust their figures less than they should be). We then apply a different unsmoothing parameter for different market growth states:

- 0.40 and 0.60 for respectively annual and monthly returns included between the average return and the average return plus its standard deviation;
- 0.50 and 0.70 for returns included between the average return plus its standard deviation and the average return plus twice its standard deviation;
- 0.60 and 0.80 for returns above the average return plus twice its standard deviation.
- 0.45 and 0.65 for respectively annual and monthly returns included between the average return and the average return minus its standard deviation;
- 0.55 and 0.75 for returns included between the average return minus its standard deviation and the average return minus twice its standard deviation;
- 0.65 and 0.85 for returns below the average return minus twice its standard deviation.

Unsmoothed capital growth rates are computed as for a first order autoregressive filter, but with varying unsmoothing parameters:

$$ucg_t = \frac{[cg_t - \alpha_1 * cg_{t-1}]}{(1 - \alpha_1)}$$

The previous methodology is also used to obtain unsmoothed income returns

$$\left(uir_t = \frac{inc_t}{ucgi_t} \right) \text{ and unsmoothed total returns } (udre_t = ucg_t + uir_t).$$

3.2.3 Index comparison

Initially, we analyse *index behaviours* of the original and unsmoothed²⁶ IPD index and both original and WACC-adjusted vehicle-based index – Datastream Real Estate sector for the annual frequency and FTSE 350 Real Estate sector for the monthly frequency – to verify if they represent similar cyclical patterns (i.e. peaks, uprising and down-falling phases).

We then investigate main *descriptive statistics* (e.g. mean, median, standard deviation, kurtosis, skewness and autocorrelation function) in order to determine the shape of each return distribution. In particular normality is tested with a Jarque Bera test (i.e. difference in shape, skewness and kurtosis), which is computed as follows:

$$JB = \frac{N - k}{6} * \left(S^2 + \frac{K - 3}{4} \right)$$

where :

N = number of observations

k = number of estimated coefficients to create the series

S = skewness

K = kurtosis

The null hypothesis of normality is rejected if there is not a proof of the opposite (i.e. the distribution is not normal). Then, having assigned a required significance level p (e.g. 5%), if the test gives a probability lower than p , the hypothesis of normality will be

²⁶ We use a first order autoregressive filter, see Geltner [1993b].

rejected (i.e. there is a lower than 5% probability that the null hypothesis will be verified). On the contrary, if the probability is higher than that level, the distribution will be considered normally distributed.

As a third step, we analyse the dependency between (both original and adjusted) securitised and unsecuritised real estate returns by using several approaches. We firstly compute three different measures of dependency to test for an existing *contemporaneous relationship* between indices.

The Pearson's correlation coefficient is a parametric measure of linear association:

$$\frac{\sum (X - \bar{X}) * (Y - \bar{Y})}{\sqrt{\frac{\sum (X - \bar{X})^2}{n}} * \sqrt{\frac{\sum (Y - \bar{Y})^2}{n}}}$$

The Kendall's Tau measures the difference between the probability of association and the probability of disassociation:

$$k_{x,y} = P[(x_1 - x_2)(y_1 - y_2) > 0] - P[(x_1 - x_2)(y_1 - y_2) < 0]$$

The product of the two differences in values is greater than zero if both $[(x_1 - x_2)$ and $(y_1 - y_2)]$ are either positive or negative (i.e. concordance). Vice versa, the product of the two differences in values is lower than zero if the two terms show opposite signs (i.e. discordance).

Finally, the Spearman's Rho relates the order of data points in the series rather than their absolute values:

$$s_{x,y} = \frac{\sum_{i=1}^n (A_i - \bar{A})(B_i - \bar{B})}{\sqrt{\sum_{i=1}^n (A_i - \bar{A})^2} \sqrt{\sum_{i=1}^n (B_i - \bar{B})^2}}$$

where :

A_i and B_i are respectively the ranks of x_i and y_i

This measure is to be preferred to a simple Pearson's correlation coefficient because it is not influenced by outliers (issue even more important when the number of observations is small) and the scale of numbers, and it also allows for non-linearity in the dependency.

We then proceed to test for *inter-temporal relationships*, firstly by computing the same three dependency measures with lagged series (up to 3 leads/lags for an annual frequency and to 12 for a monthly one), and secondly by applying a Granger causality test. The following bivariate VAR model is applied to both adjusted and original time series:

$$r_{n,t} = \alpha_n + \sum_{i=1}^p \beta_{n,i} r_{n,t-i} + \sum_{i=1}^p \theta_{a,i} r_{a,t-i} + \varepsilon_{n,t}$$

and

$$r_{a,t} = \alpha_a + \sum_{i=1}^p \beta_{a,i} r_{a,t-i} + \sum_{i=1}^p \theta_{n,i} r_{n,t-i} + \varepsilon_{a,t}$$

where $r_{s,t}$ represents the return of new ($s=n$) and actual ($s=a$) indices, p is the number of lags to be considered (2 and 12 respectively for annual and monthly data), α_s is the

intercept, $\beta_{s,i}$ the autoregressive parameter of order j , and $\theta_{s,i}$ represents the coefficient measuring the causality of the j^{th} lag return. The Granger causality test is then performed through an F-test with the following null hypothesis:

$$\theta_{s,i} = 0 \quad \forall i$$

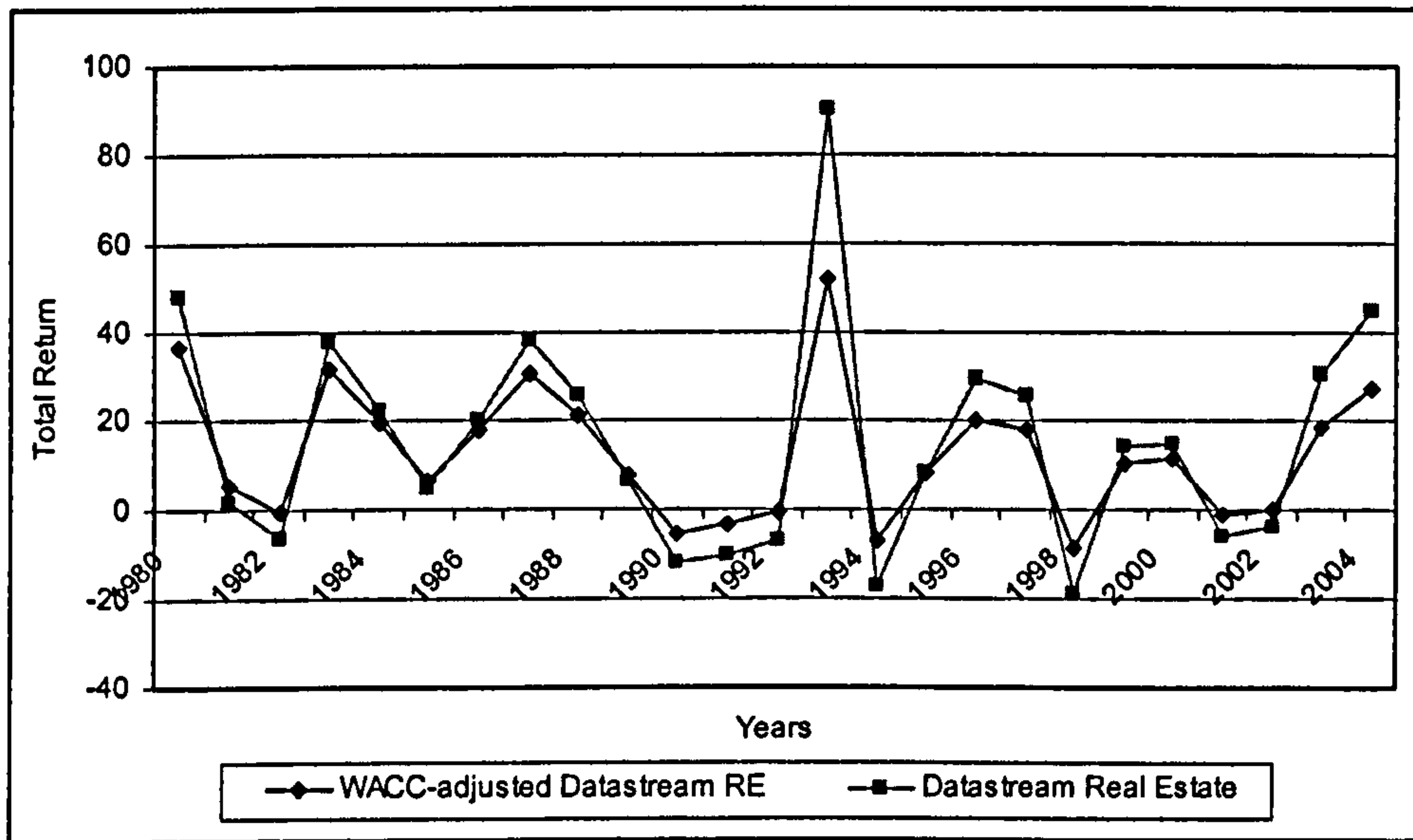
If the null hypothesis is rejected, we conclude that returns of index n are Granger caused by returns of index a (or vice versa). This is the same to say that the rejection of the null hypothesis verifies the existence of a cross predictability (i.e. the ability of past values of one series to predict contemporaneous values of the other series). This particular test is useful mostly when indirect and direct real estate indices are compared because of the different speed with which the two markets process new information.

3.3 RESULTS

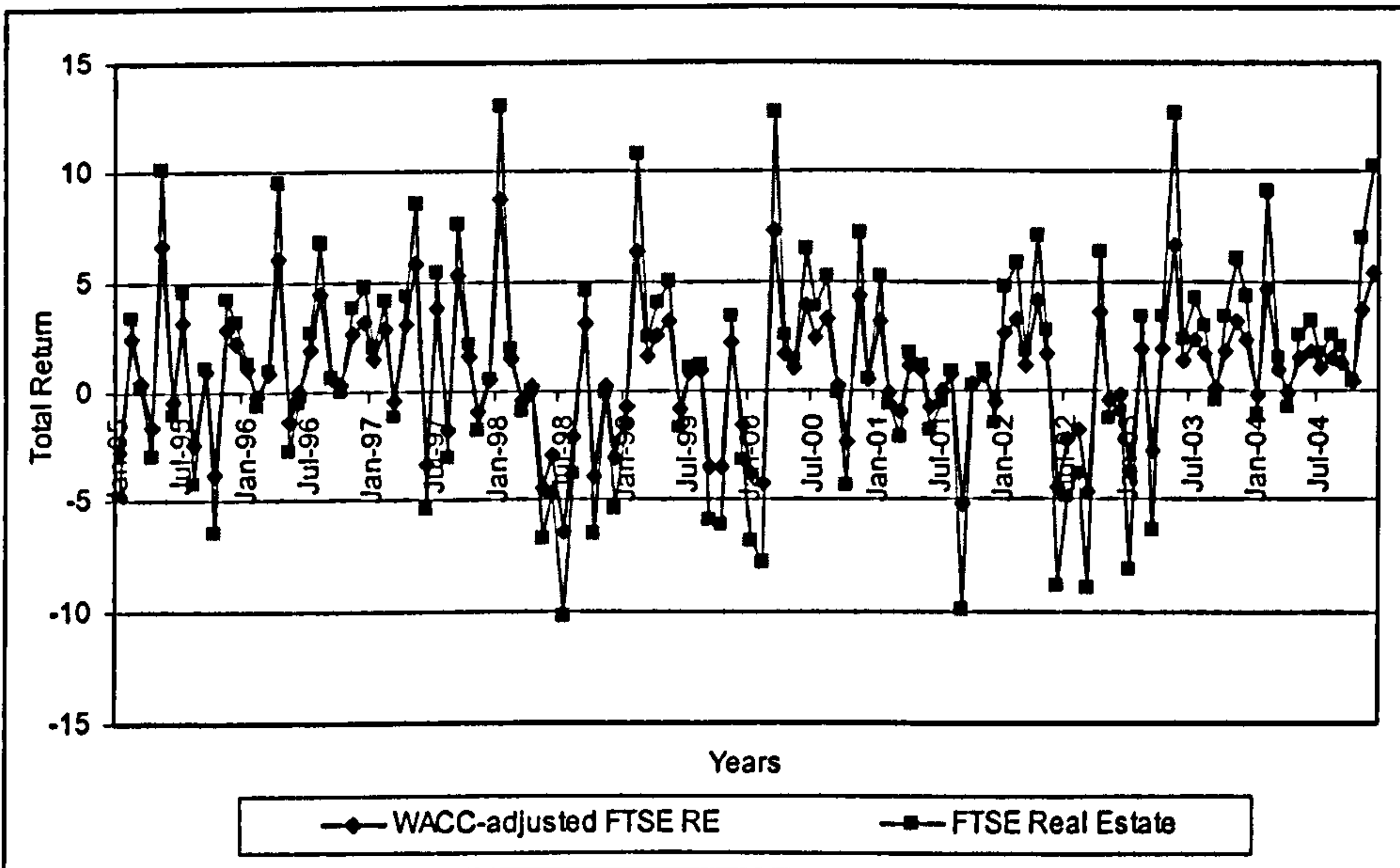
3.3.1 The effects of unsmoothing and de-gearing

Graph 3.1 and 3.2 show the performance of geared and de-geared indices respectively for annual and monthly data. The monthly FTSE 350 Real Estate returns, both geared and de-geared, along with related descriptive statistics are included in Appendix 1: being an original data source, derived from primary sources, the record of the data used for the analysis is felt to be important.

Graph 3.1: Datastream real estate and de-gearred returns (annual)



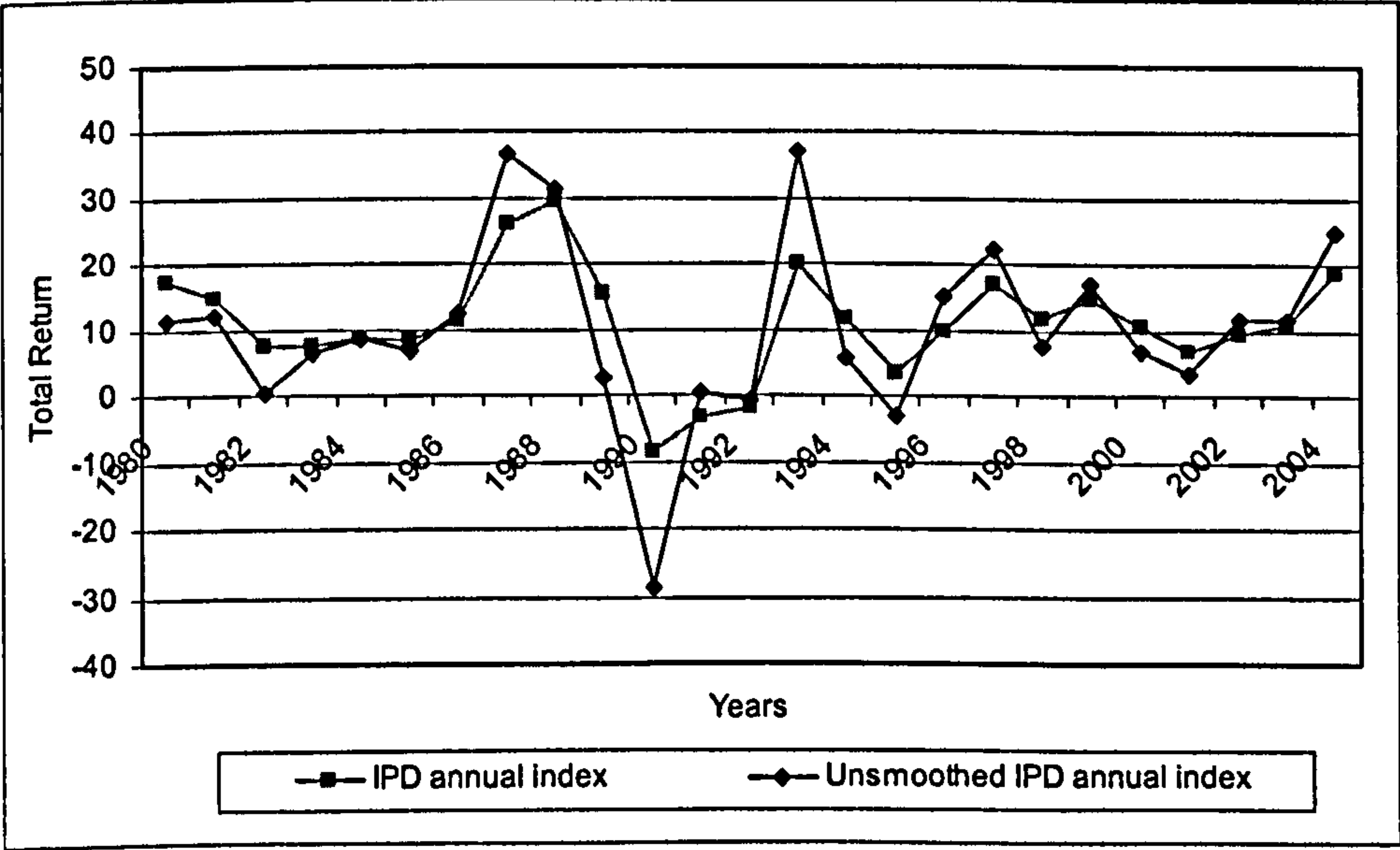
Graph 3.2: FTSE 350 real estate and de-gearred returns (monthly)



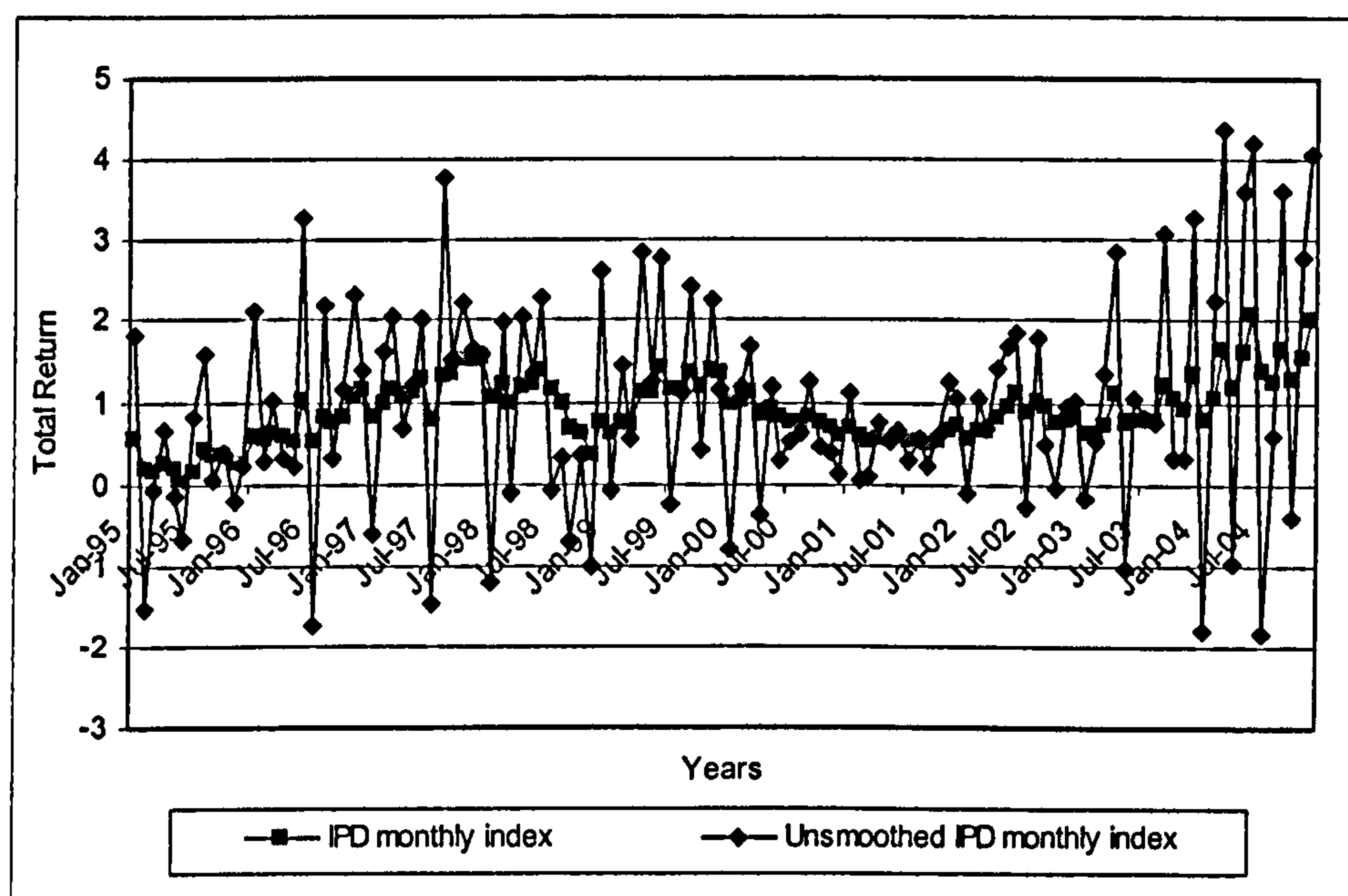
The two graphs show that de-gearred performances behave very similarly to original real estate share returns for both annual and monthly frequencies. However highs and lows are, in absolute value, clearly smaller for unlevered figures, leading to a lower index volatility (i.e. the increase of gearing should increase the risk of an investment). This is precisely the result we would expect because gearing should only affect the volatility when the cost of capital debt is similar to real estate returns.

Graphs 3.3 and 3.4 compare returns of original and unsmoothed IPD indices respectively for annual and monthly data. In sections 3.3.1 and 3.3.2 we only analyse unsmoothed returns obtained with a first order autoregressive filter (i.e. foarf method). Differences as a result of the application of different unsmoothing methods will be discussed in section 3.3.3.

Graph 3.3: IPD annual returns and Unsmoothed IPD annual performances (annual)



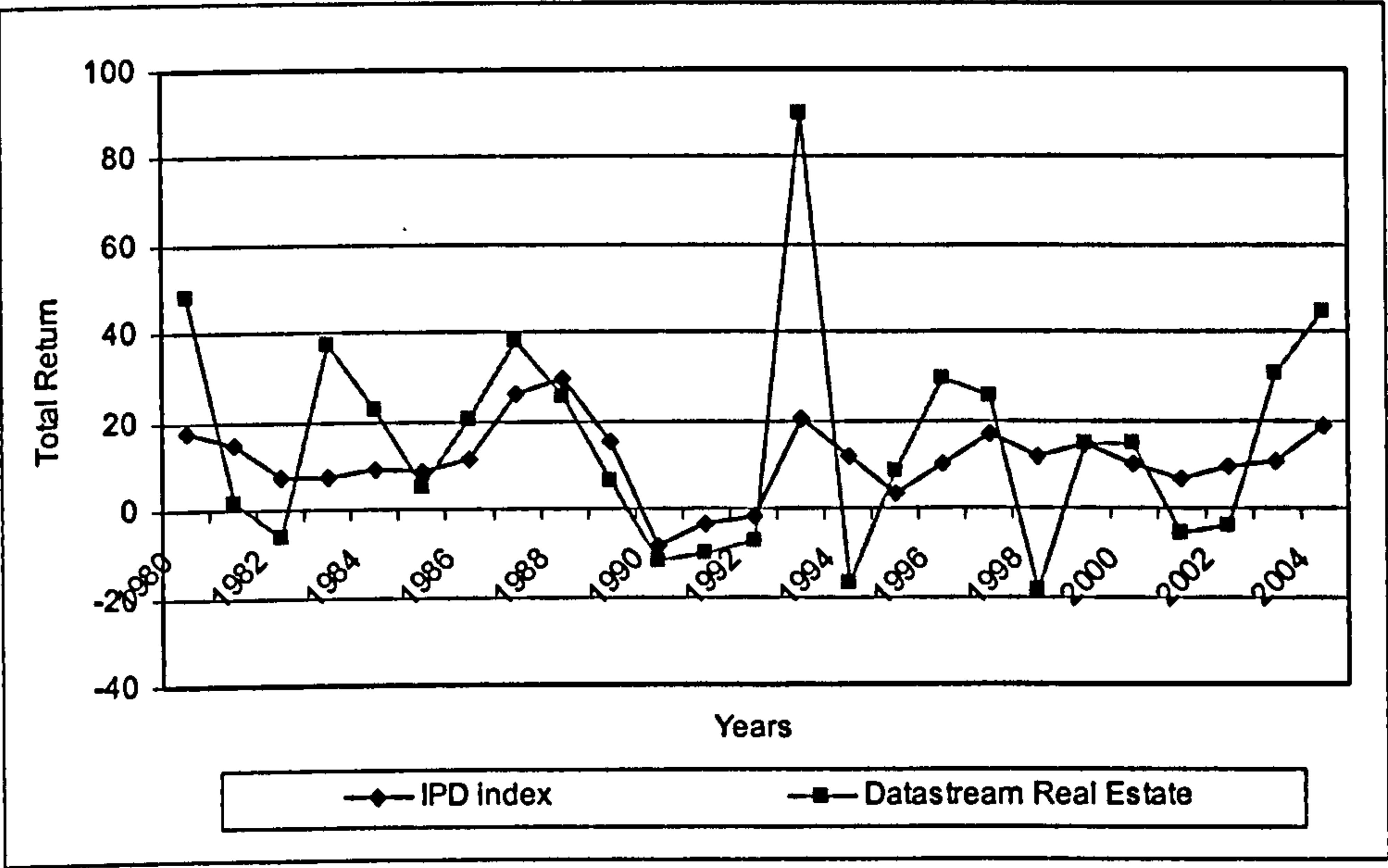
Graph 3.4: IPD annual returns and unsmoothed IPD annual performances (monthly)



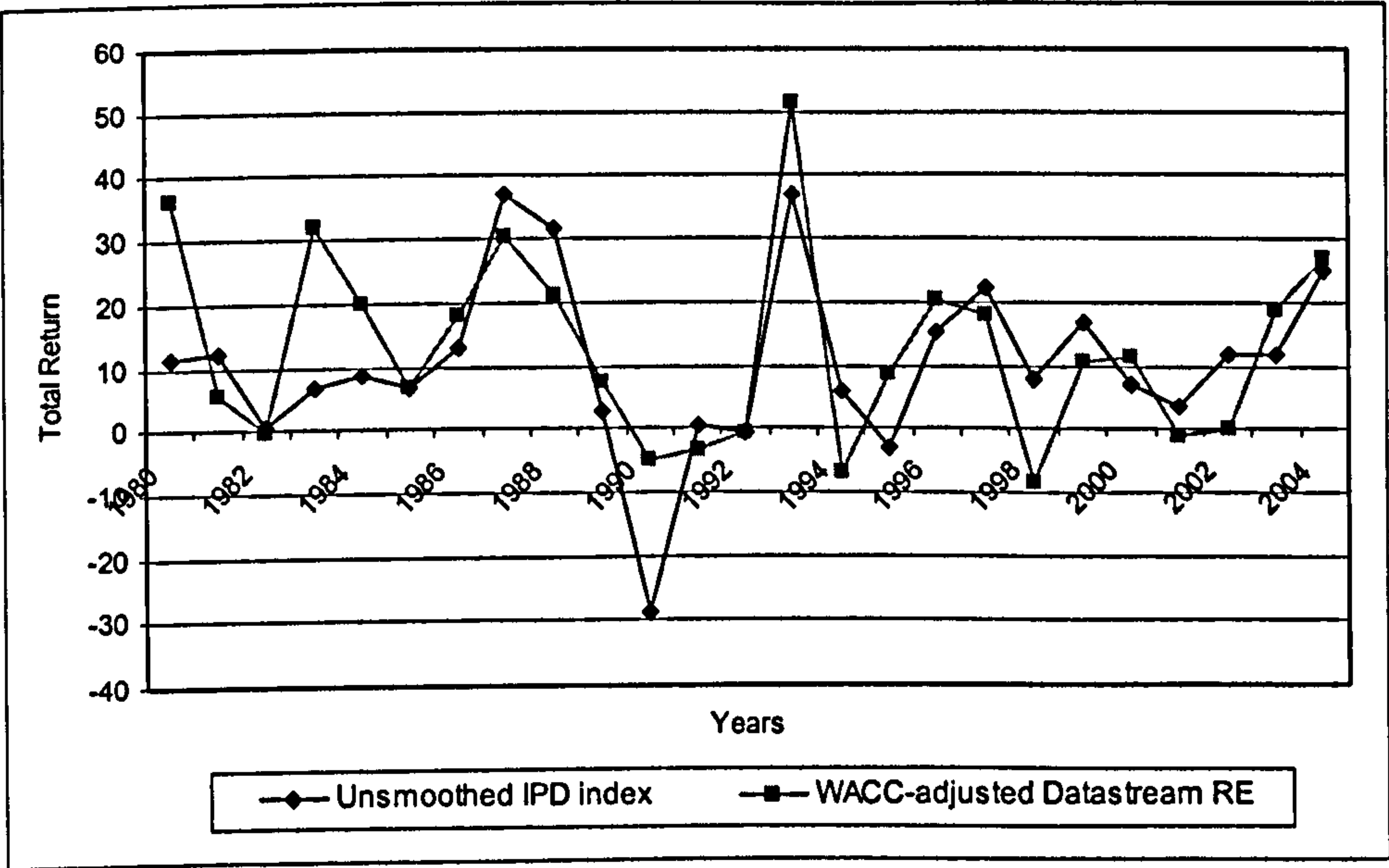
The extent of the unsmoothing impact on returns is very different for the two frequencies. While the first annual graph shows a similar behaviour between original and adjusted time series – along with a higher index volatility for the adjusted series – the second graph reveals a random unsmoothed index compared to a relatively “stable” original IPD index.

For annual data, unsmoothing and de-gearing give rise to the dependency between adjusted securitised and unsecuritised returns, and this can be seen through a closer behaviour between adjusted series (graph 3.5) than between original ones (graph 3.6). From the cyclical pattern of the types of indices, we also expect to find securitised real estate returns leading unsecuritised ones. On the other hand, with a monthly frequency, this improvement is not clear and needs further investigation. (see graphs 3.7 and 3.8).

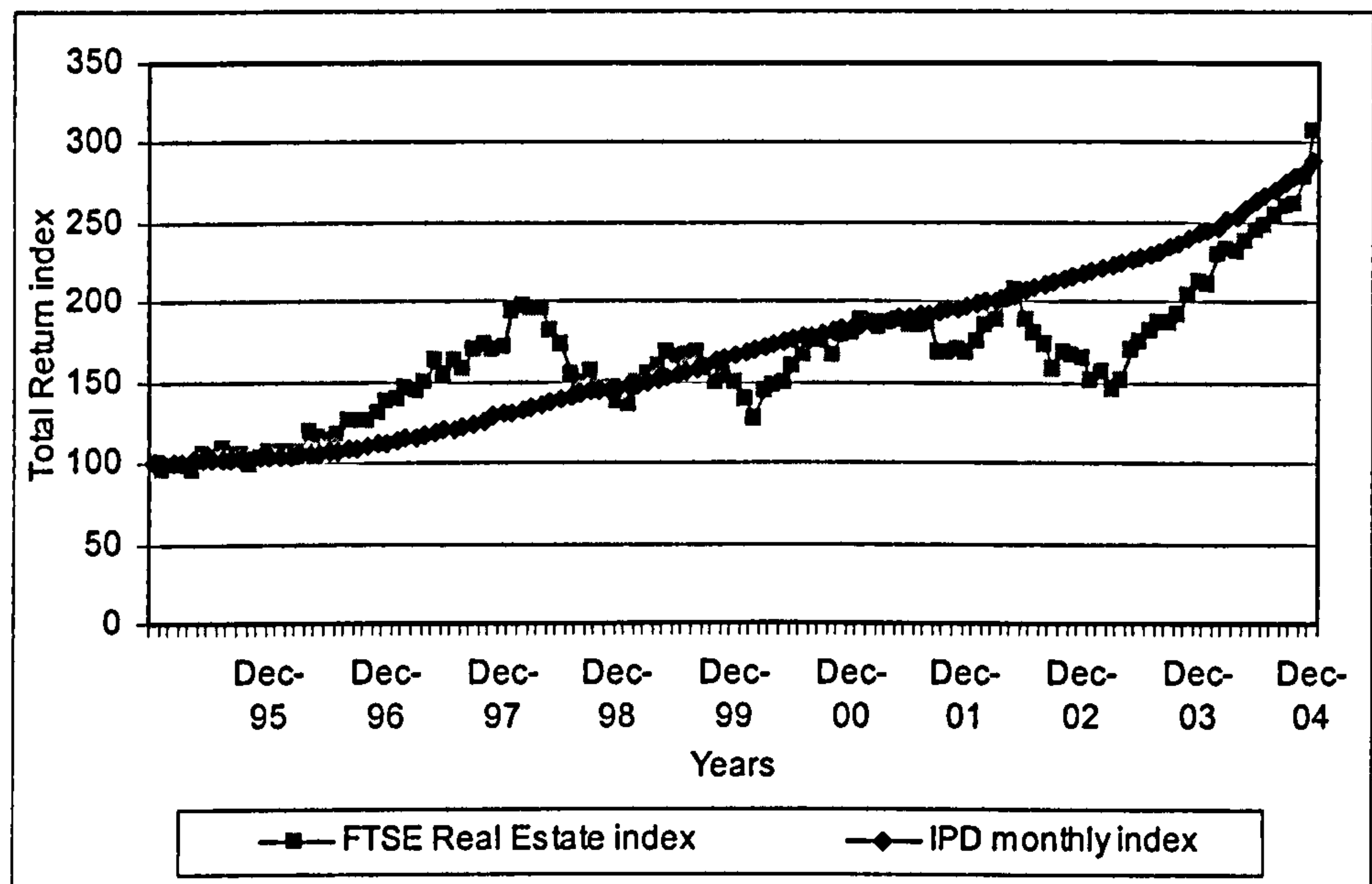
Graph 3.5: IPD performances and Datastream real estate returns (annual)



Graph 3.6: Unsmoothed IPD returns and de-geared securitised returns (annual)



Graph 3.7: IPD index and FTSE real estate index (monthly)



Graph 3.8: Unsmoothed IPD index and de-geared FTSE Real Estate index (monthly)

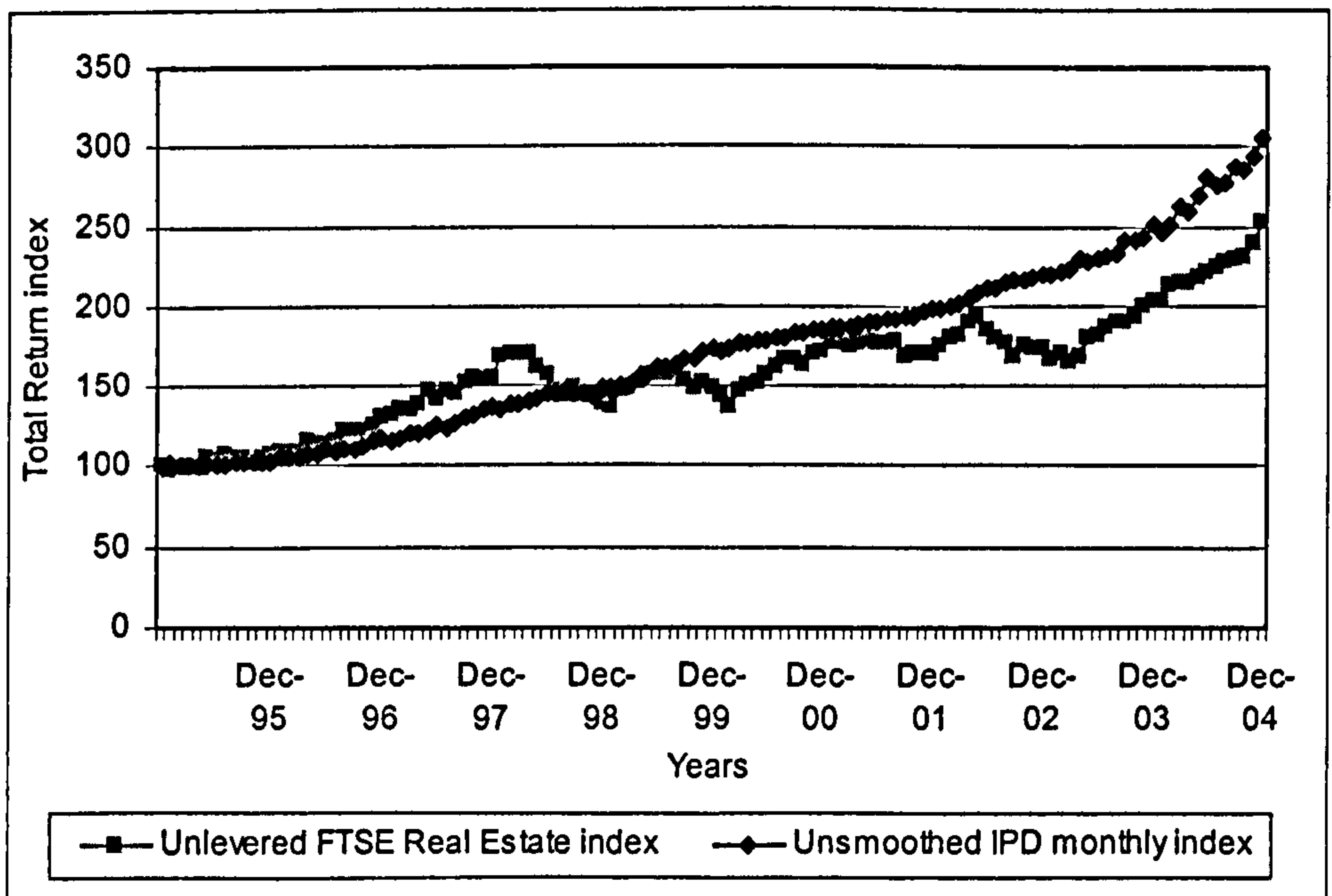


Table 3.1: Descriptive statistics for geared and de-geared indirect real estate indices

	Annual Data		Monthly Data	
	FTSE Real Estate Total Return	De-geared FTSE RE Total Return	FTSE Real Estate Total Return	De-geared FTSE RE Total Return
Mean	15.35	12.73	1.06	0.82
Median	14.49	10.69	1.15	0.92
Maximum	90.09	51.58	12.95	8.76
Minimum	-18.57	-8.63	-10.29	-6.49
Standard Deviation	24.98	15.10	4.90	2.85
Skewness	0.98	0.65	0.00	0.00
Kurtosis	4.23	2.95	2.96	3.06
Jarque-Bera	5.55	1.74	0.01	0.02
Probability	0.06	0.42	1.00	0.99
Partial Autocorrelation				
Lag 1	-0.18	-0.11	0.05	0.03
Lag 2	-0.35	-0.33	0.07	0.08
Lag 3	0.02	0.06	0.12	0.11
Lag 4			0.00	0.01
Lag 5			-0.03	-0.01
Lag 6			-0.04	-0.07
Lag 7			-0.07	-0.09
Lag 8			-0.06	-0.04
Lag 9			0.04	0.03
Lag 10			-0.15	-0.16
Lag 11			-0.15	-0.11
Lag 12			0.04	0.01

Table 3.1 reports main descriptive statistics for both annual and monthly total returns of original and de-geared real estate share prices. The average return for the annual real estate index and the de-geared one is respectively 15.35% pa and 12.73% pa (i.e. the transformation leads to a lower mean). A plausible explanation for the closeness of these two figures can be found in a rate of return from real estate – over the data period – that is probably very similar to (and probably lower than) the cost of debt capital.

However, when the index is de-gearred, the standard deviation of returns decreases from 24.98% to 15.10%. This is exactly the result that we would expect: the less property companies finance their assets by issuing debt (external capital), the lower the risk perceived by investors.

The average return for the monthly index is 1.06% per month and its standard deviation equals 4.90%. When the index is de-gearred, these two figures respectively move to 0.82% pm and 2.85%.

3.3.2 Private and public real estate returns: a comparison

This section contains results of the comparison between the WACC-adjusted vehicle-based index and unsmoothed (obtained through a first order autoregressive filter) valuation-based indices.

Tables 3.2 and 3.3 show the measures of dependency between the four different series (i.e. smoothed and unsmoothed IPD, and geared and de-gearred property companies returns). All measures of dependency suggest the same pattern.

For the annual data, unsmoothing valuation-based indices leads to a substantially closer relationship with vehicle-based indices. Instead, de-gearing the real estate equity index makes little difference to the relationship with either the original or the unsmoothed direct index (as we would expect since de-gearing only reduces the volatility of the indirect index). The correlation coefficient increases, as a result of unsmoothing from a level broadly similar to that which exists between two closely connected equity markets

(for example the UK and US markets) to a much higher level. If we assume that the technique of unsmoothing leads to the creation of a direct real estate index that is closer to the underlying transaction-based index, the result suggests that there is significant information content in the indirect real estate indices about the direct market. Therefore, vehicle-based indices may be used to retrieve private real estate returns in markets with thin information, where a very small amount of direct property data is available. In these markets, in fact, property vehicles normally exist and their performances may be adjusted with a WACC model to obtain a proxy for real estate market returns.

Tests of cointegration were carried out in order to find whether the long-run equilibrium relationship between the two types of indices changes as a result of unsmoothing and de-gearing. These tests were inconclusive because of the lack of data reducing their power.

Table 3.2: Dependency measures between real estate indices (annual)

	Correlation Coefficient	Kendall Tau	Spearman Rho
IPD vs. real estate shares	0.61	0.49	0.62
Unsmoothed IPD vs. Unlevered real estate shares	0.79	0.59	0.78
Unsmoothed IPD vs. real estate shares	0.75	0.54	0.75
IPD vs. Unlevered real estate shares	0.66	0.52	0.66

Table 3.3: Dependency measures between real estate indices (monthly)

	Correlation Coefficient	Kendall Tau	Spearman Rho
IPD vs. real estate shares	0.04	0.03	0.04
Unsmoothed IPD vs. Unlevered real estate shares	-0.01	0.01	0.02
Unsmoothed IPD vs. real estate shares	0.01	0.02	0.03
IPD vs. Unlevered real estate shares	0.02	0.02	0.02

In the case of monthly frequencies, all measures suggest a lack of dependency between different indices (i.e. they are not significantly different from zero). Moreover, unsmoothing and de-gearing do not improve these measures.

From this result, one of two conclusions can be reached: either the monthly index for the direct market does not properly represent the underlying performance of transactions taking place in the direct market – and this being true even when the index is unsmoothed – or the de-gearred monthly index for the indirect market does not provide useful information about the direct market because it is affected by “equity noise”. On the one hand a different investment horizon and investors acting with a speculative attitude could form the basis to believe the second explanation. However, dependency ratios not even having minimally improved by these adjustments and showing dependencies not significantly different from zero may strengthen the validity of a

strong *a priori* case for assuming the former. The issues of stale appraisals and valuation smoothing are much more acute for a monthly frequency than for an annual one. Therefore, the capability of direct monthly indices to properly represent the underlying process of transaction prices does not seem plausible, even when standard techniques (i.e. unsmoothing) are applied to transform the data. The adjusted indirect performance then represents a valid source of information that is complementary to the one offered by valuation-based indices.

With an annual frequency the WACC model shows similar statistics and a higher than original dependency between adjusted performances in direct and indirect property markets. If the frequency is monthly much more similar statistics arising from the application of these models do not find an adequate confirmation in the dependency measure. This suggests two possible reasons: either the higher frequency reveals a different investment horizon (i.e. every month the investor in property vehicles is not concerned about fundamentals driving the real estate market, but about speculative opportunities linked to equity market effects), or the adjusted performance of vehicle-based indices contains useful information. The very fact that any degree of dependency does not exist between unsmoothed direct property returns and adjusted vehicle-based ones probably indicates that a combination of the two motivations exists and should be further investigated.

3.3.3 Sensitivity of results on unsmoothing technique and parameter

Table 3.4 shows descriptive statistics for several annual indices. No main differences are found when different unsmoothing techniques are applied, and figures are very similar to the one shown by the adjusted indirect index. Average unsmoothed direct property returns range between 11.33% (foarf) and 13.14% (states) and are similar to the IPD one (11.31%), while standard deviations range between 11.61% (noarf) and 24.39% (states) and are then generally higher than the original one (9.71%). Consequently the return per unit of risk falls by around 0.5 points, from 1.17 to 0.54 for “states” and 0.70 for “foarf” and “fivi”.

Finally, all series pass the Jarque-Bera normality test, showing a slightly negative skewness and a kurtosis around 3.0.

Table 3.4: Average return and standard deviation of annual total returns

	Mean	Standard Deviation	Return per unit of risk	Skewness	Kurtosis
lpd	11.31	9.71	1.17	-0.18	2.79
foarf	11.33	16.16	0.70	-0.38	3.58
fivi	11.34	16.13	0.70	-0.38	3.58
states	13.14	24.39	0.54	-0.46	3.86
noarf	12.95	11.61	1.12	-0.15	2.54
ds rest	14.16	27.18	0.52	1.12	4.32
wacc	11.11	15.65	0.71	0.86	3.47

Table 3.5: Pearson’s correlation coefficient for annual total returns

	lpd	foarf	fivi	states	noarf	ds rest	wacc
lpd	1.00						
foarf		1.00					
fivi			1.00				
states				1.00			
noarf					1.00		
ds rest	0.61	0.75	0.75	0.76	0.77	1.00	
wacc	0.66	0.79	0.79	0.79	0.81		1.00

Table 3.6: Kendall’s tau for annual total returns

	lpd	foarf	fivi	states	noarf	ds rest	wacc
lpd	1.00						
foarf		1.00					
fivi			1.00				
states				1.00			
noarf					1.00		
ds rest	0.49	0.54	0.54	0.56	0.58	1.00	
wacc	0.52	0.59	0.59	0.63	0.63		1.00

Table 3.7: Spearman ratio for annual total returns

	lpd	foarf	fivi	states	noarf	ds rest	wacc
lpd	1.00						
foarf		1.00					
fivi			1.00				
states				1.00			
noarf					1.00		
ds rest	0.62	0.75	0.75	0.75	0.78	1.00	
wacc	0.66	0.78	0.78	0.79	0.81		1.00

Tables 3.5 to 3.7 show, for an annual frequency, dependency measures between original IPD and Datastream indices and adjusted series. Particularly, we are interested in figures of dependency between degearred vehicle-based indices (WACC approach, i.e. deg) and different unsmoothed series (the n^{th} order autoregressive filter has not been applied to annual returns). As shown from all measures of dependency, the unsmoothing technique using market growth states is the only one with which we do not find any improvement in the linkage between direct and indirect performances when indices are adjusted. The other two unsmoothing procedures give similar results.

Table 3.8: Average return and standard deviation of monthly total returns

	Mean	Standard Deviation	Return per unit of risk	Skewness	Kurtosis
ipd	0.89	0.39	2.28	0.37	3.15
foarf	0.94	1.30	0.73	0.35	3.09
foarf v	0.93	1.44	0.65	-0.14	3.38
fivi	1.19	2.43	0.49	0.36	3.10
states	0.96	1.54	0.62	0.28	3.09
noarf	1.01	2.01	0.50	0.60	3.66
ds rest	1.06	4.90	0.22	0.00	2.96
wacc	0.82	2.85	0.29	0.00	3.06

Monthly returns show a different picture (see table 3.8). If the average is similar for all unsmoothed returns and it is not very different from the original one, standard deviation figures vary. The volatility weight model obtains a risk measure that is double (or three

times) the one shown by other unsmoothed indices. However, with all techniques, its value is at least three times bigger than the original IPD one, signalling the great importance of the valuation smoothing issue when a monthly frequency is used.

Table 3.9: Pearson’s correlation coefficient for monthly total returns

	ipd	foarf	foarf v	fivi	states	noarf	ds rest	wacc
ipd	1.00							
foarf		1.00						
foarf v			1.00					
fivi				1.00				
states					1.00			
noarf						1.00		
ds rest	0.04	0.01	-0.05	0.02	0.01	0.01	1.00	
wacc	0.02	-0.01	-0.08	-0.01	-0.02	-0.01		1.00

Table 3.10: Kendall’s tau for monthly total returns

	ipd	foarf	foarf v	fivi	states	noarf	ds rest	wacc
ipd	1.00							
foarf		1.00						
foarf v			1.00					
fivi				1.00				
states					1.00			
noarf						1.00		
ds rest	0.03	0.02	0.01	0.02	0.02	0.01	1.00	
wacc	0.02	0.01	0.00	0.01	0.01	0.00		1.00

Table 3.11: Spearman ratio for monthly total returns

	ipd	foarf	foarf v	fivi	states	noarf	ds rest	wacc
ipd	1.00							
foarf		1.00						
foarf v			1.00					
fivi				1.00				
states					1.00			
noarf						1.00		
ds rest	0.04	0.03	0.02	0.03	0.03	0.02	1.00	
wacc	0.02	0.02	0.00	0.01	0.02	0.00		1.00

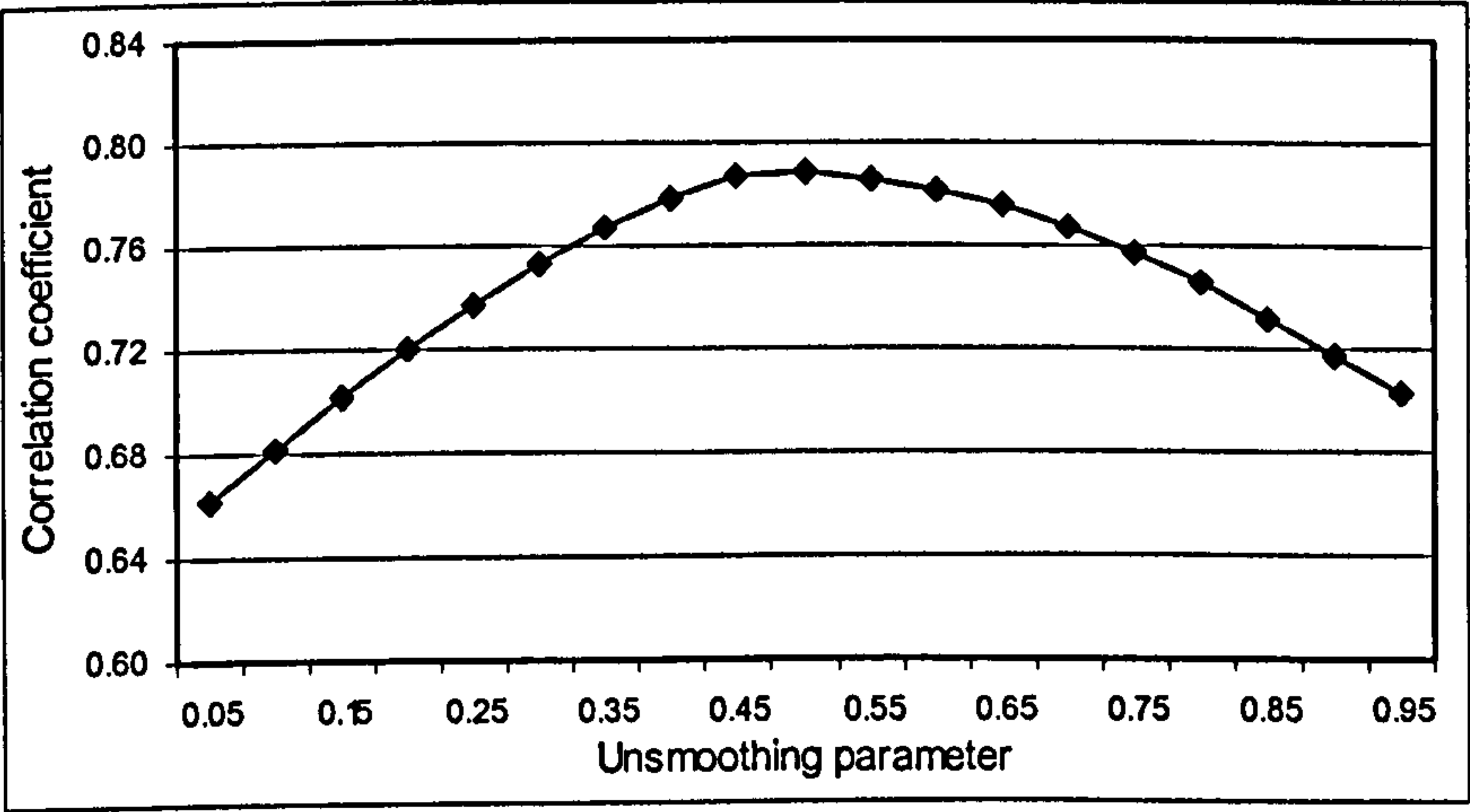
Tables 3.9 to 3.11 show dependency measures between original IPD and Datastream indices and adjusted series. As shown from all measures of dependency, there does not seem to exist any sort of relationship between direct and indirect performances even if these are adjusted. This result holds regardless the unsmoothing technique used to adjust the valuation-based index.

Finally, we show that by changing the smoothing parameter, we do not obtain significant variations in the dependency measure. When plausible unsmoothing parameter ranges are considered – e.g. [0.35 - 0.70] – correlation coefficients computed with annual capital growth rates are all found around 0.70.

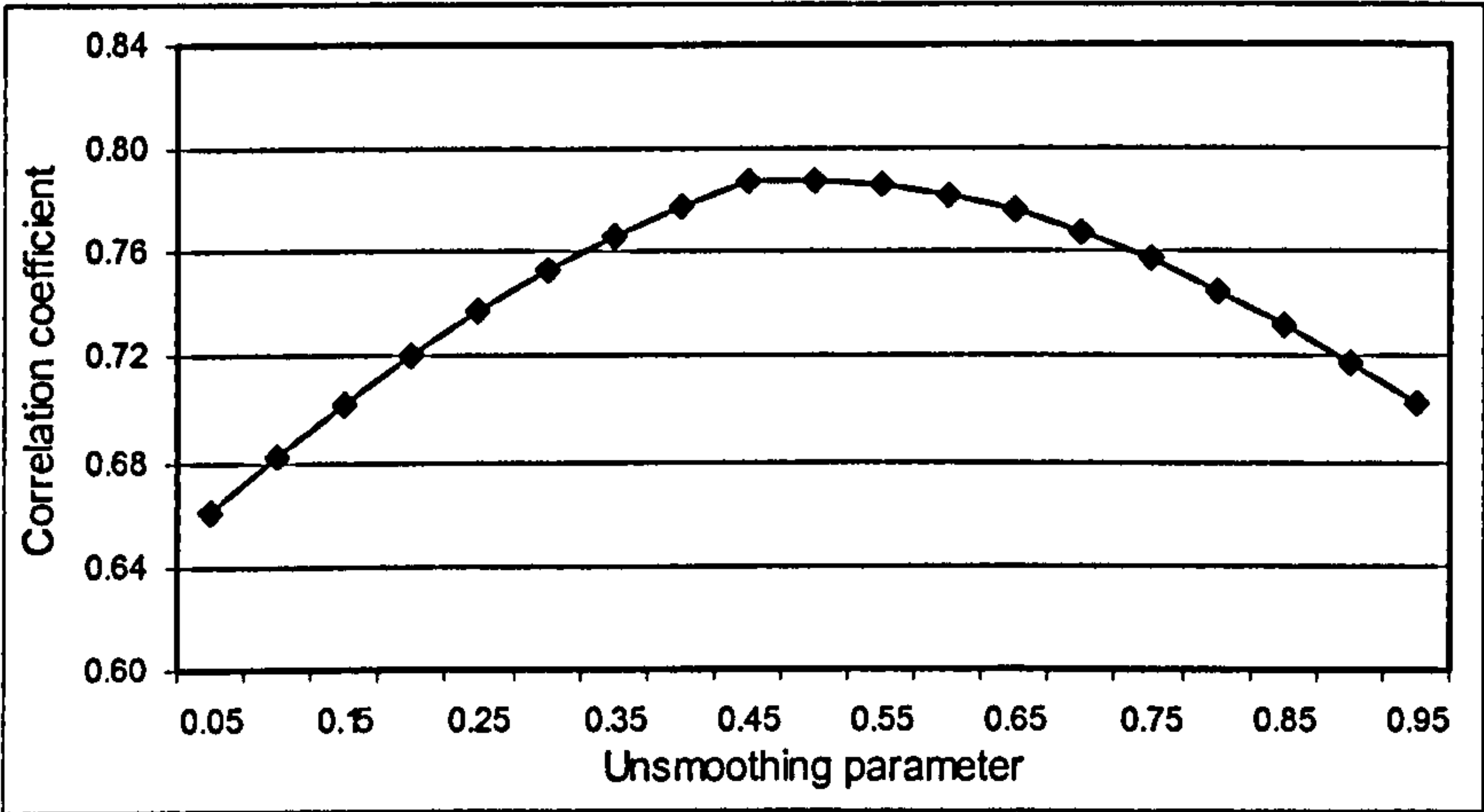
Graphs 3.9 to 3.12 show – respectively for foarf, fivi, states and noarf unsmoothing techniques – the variation of the correlation coefficient between adjusted annual capital growth rates, when the unsmoothing parameter changes.

All these graphs demonstrate that the choice of the unsmoothing technique is not relevant and does not have any impact on the correlation found between adjusted securitised and unsecuritised property returns. Moreover, the correlation coefficient reaches a point of maximum in correspondence of unsmoothing parameters which change from model to model. If we consider the first order autoregressive filter, this parameter is in line with the one used in the literature. We think this result is very important because unsmoothing parameters are normally arbitrarily chosen. The use of a parameter equal to either 0.50 or 0.55 (i.e. this is the weight the valuer attributes to old information) maximises the correlation between direct and indirect markets, suggesting that previous studies chose an adequate parameter to unsmooth private real estate performances.

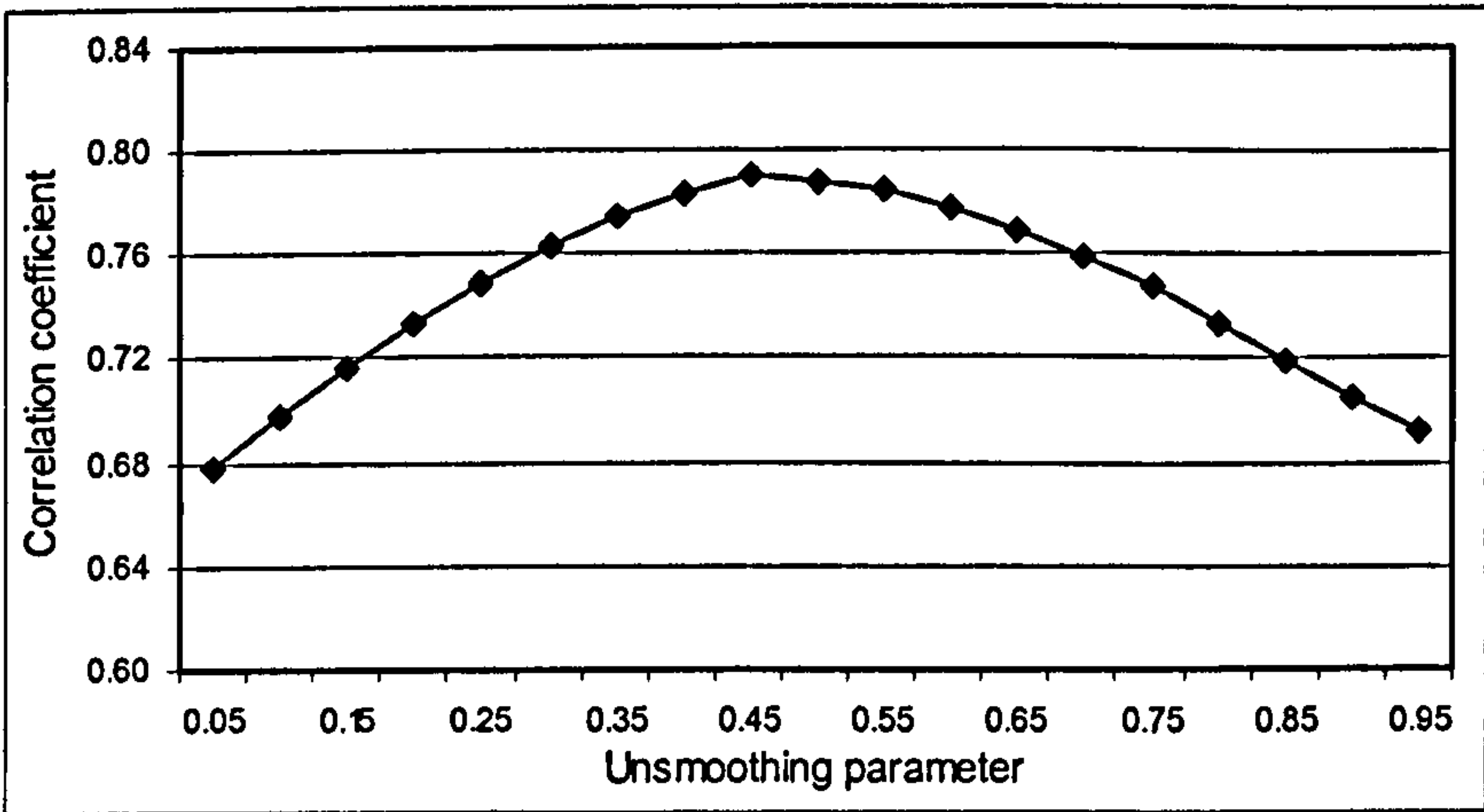
Graph 3.9: Impact of unsmoothing parameters on correlation coefficients (foarf - a)



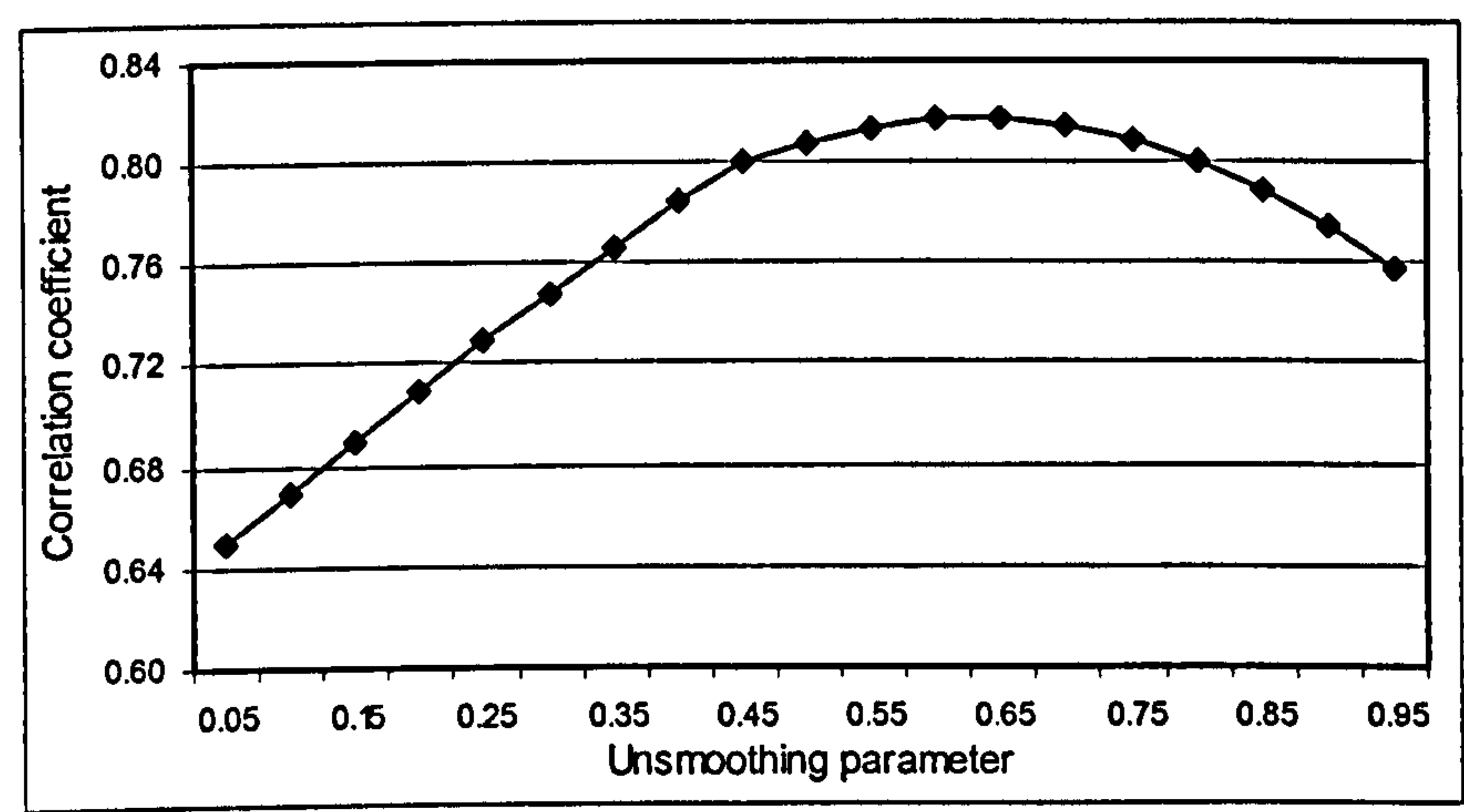
Graph 3.10: Impact of unsmoothing parameters on correlation coefficients (fivi - a)



Graph 3.11: Impact of unsmoothing parameters on correlation coefficients (states - a)

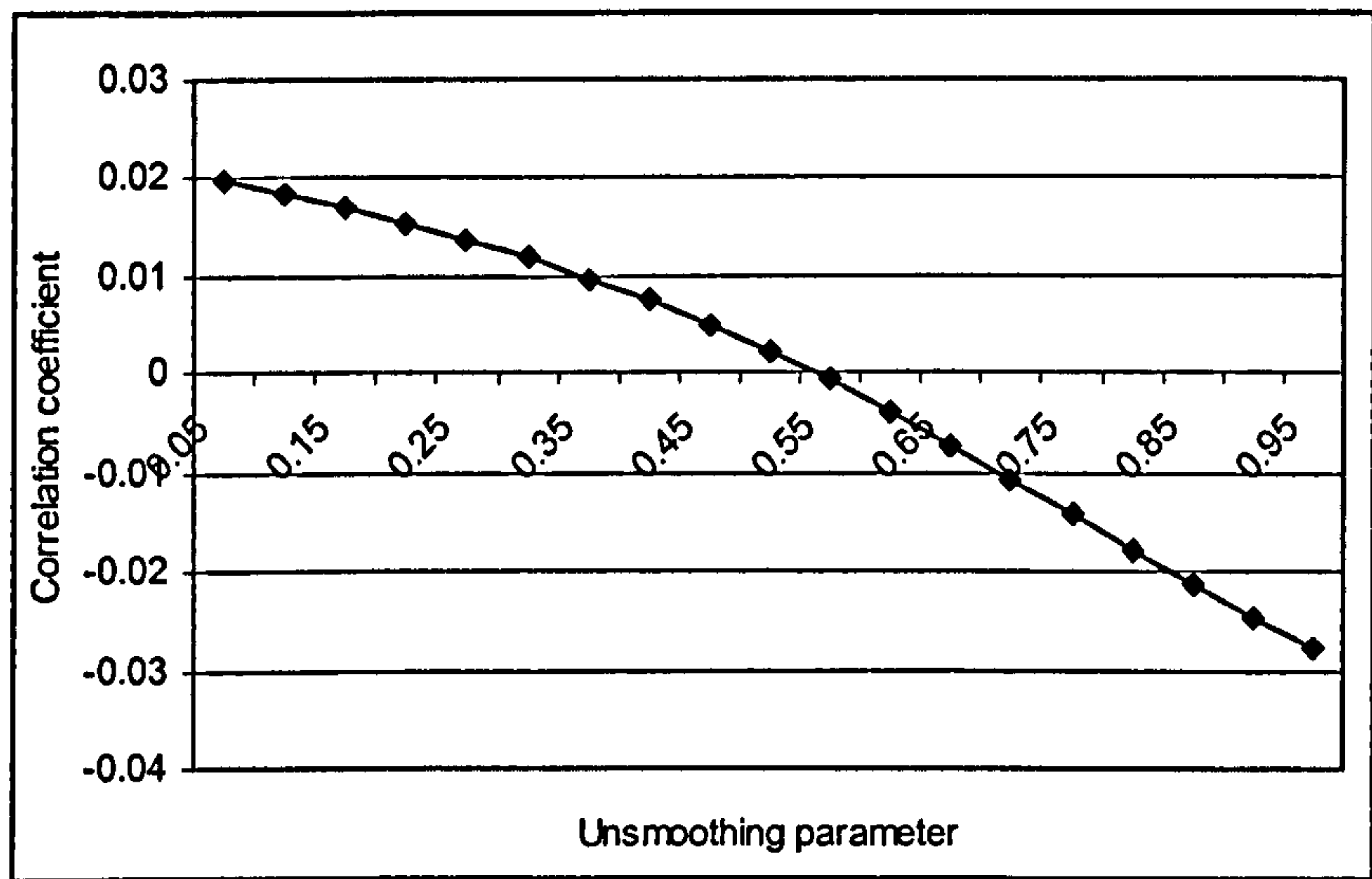


Graph 3.12: Impact of unsmoothing parameters on correlation coefficients (noarf - a)

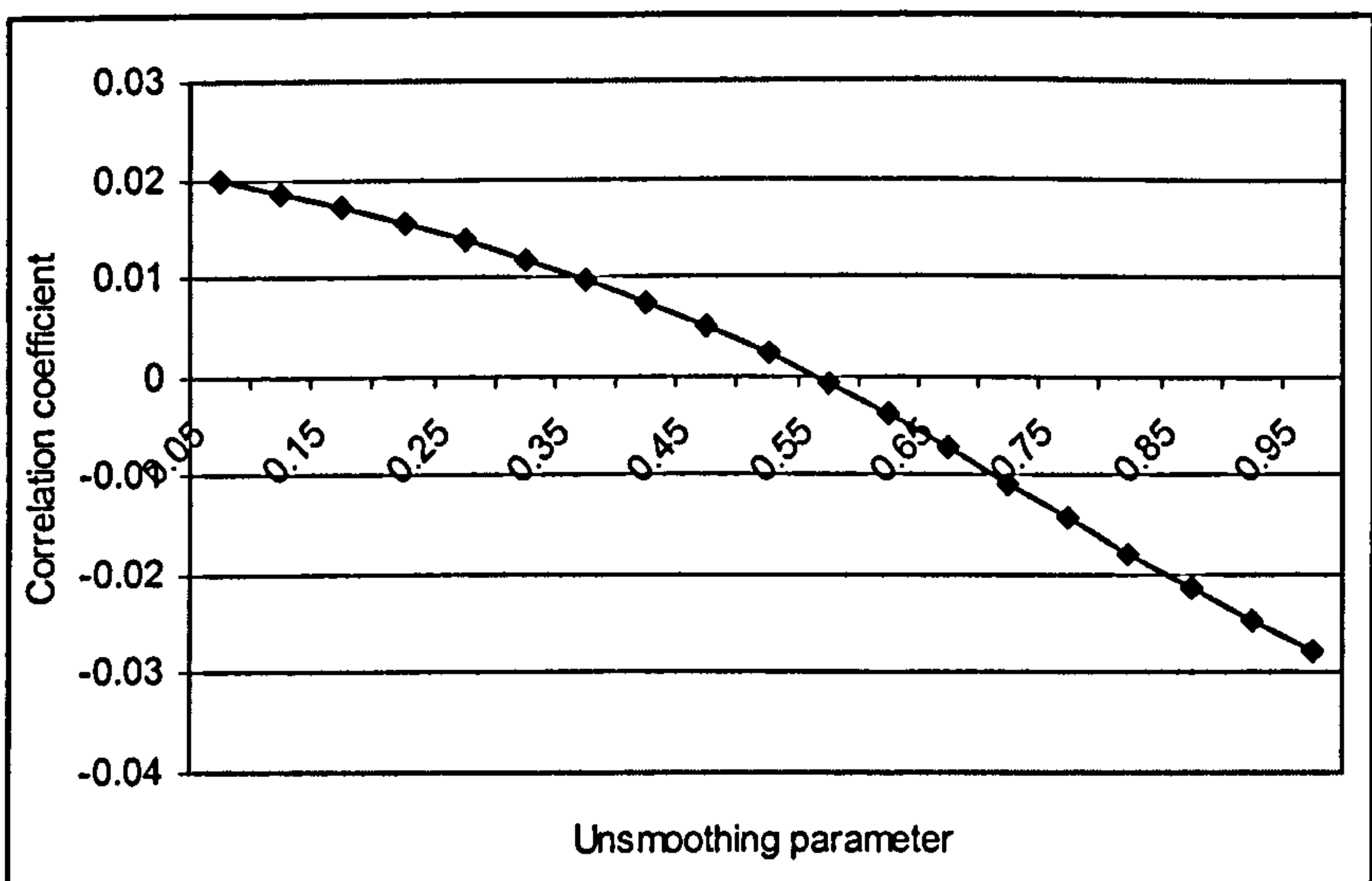


Finally, graphs 3.13 to 3.16 show the same sensitivity analysis for monthly capital growth rates. Correlation coefficients do not significantly differ from zero for any unsmoothing technique and parameter used.

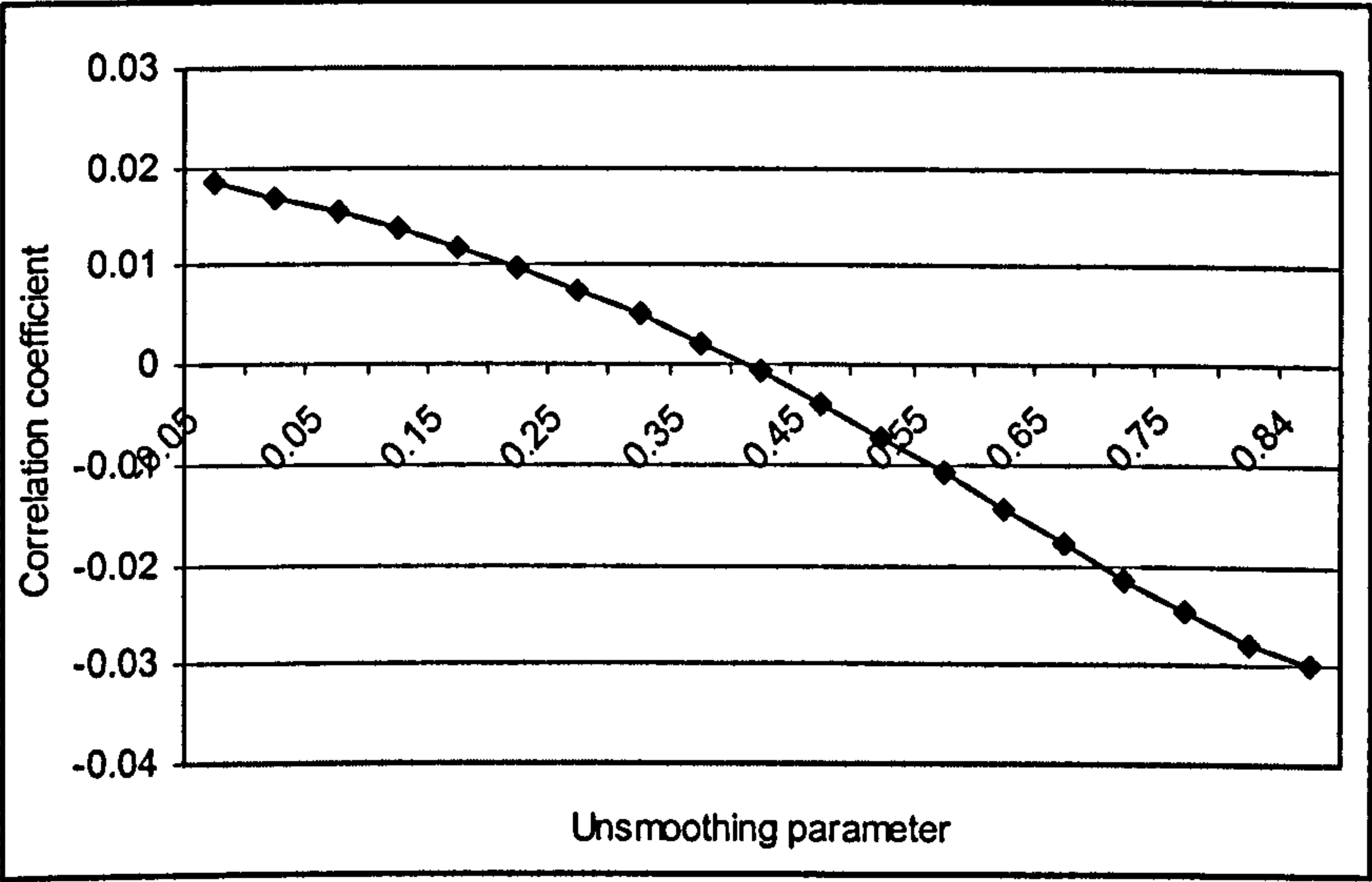
Graph 3.13: Impact of unsmoothing parameters on correlation coefficients (foarf - m)



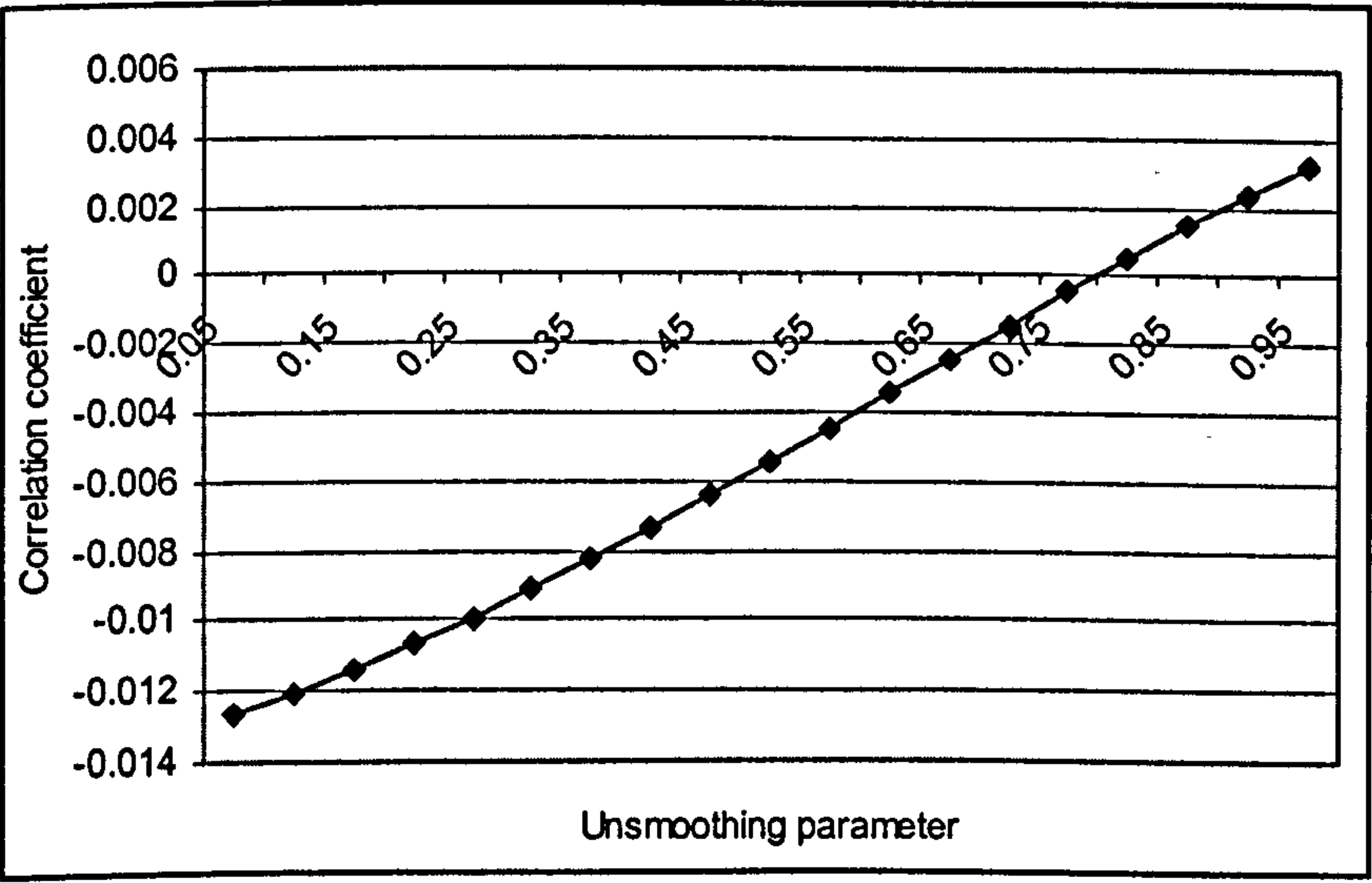
Graph 3.14: Impact of unsmoothing parameters on correlation coefficients (fivi - m)



Graph 3.15: Impact of unsmoothing parameters on correlation coefficients (states - m)



Graph 3.16: Impact of unsmoothing parameters on correlation coefficients (noarf - m)



3.4 CONCLUSIONS

This chapter improves the real estate literature on price discovery by applying a WACC model to a vehicle-based index in order to obtain a proxy for private real estate returns. We argue this model may be used to produce indices measuring annual direct property performances in markets with thin information – i.e. in markets in which it is not possible to collect enough information on direct property investments (e.g. valuations), this framework becomes a plausible way to construct historical series of direct property returns on a yearly basis²⁷.

In fact, the empirical analysis suggests that de-gearred securitised returns have useful information content and could represent a good proxy to describe long-run performances in private real estate markets. When valuation-based indices are unsmoothed, measures of dependency between this index and adjusted indirect performances strengthen significantly. If, according to previous literature, we assume that unsmoothed direct real estate returns better reflect underlying transaction prices than original direct real estate data, our result suggests that property company data could be useful for “filling in the gaps” in direct market series.

However, if we consider a monthly frequency, the use of de-gearred real estate company data may or may not be a proxy for unobserved direct property returns. Whilst there is clearly information content in the data and vehicle-based indices are helpful in

²⁷ The correct applicability of the WACC model in markets with thin information may be limited by some key issues, which will be discussed in the final chapter (see section 6.2.1).

understanding movements in transaction prices in the direct market, when monthly data are used, no relationship between the direct real estate market (whether index values are used directly or unsmoothed returns are preferred) and the indirect market has been found. The most reasonable explanations for this feature are twofold: firstly, the equity noise (reflecting a different investment horizon and a speculative behaviour) is more relevant in monthly indices than in annual ones; secondly, monthly valuation-based indices do not reflect underlying market movements as fully as annual indices because of problems of valuation smoothing, which are intensified when higher valuation frequencies are used. If it is the second of these explanations, it would suggest that, even for a monthly frequency, the indirect market (appropriately de-g geared) can provide useful information, which is not provided by valuation-based indices. The adjusted vehicle-based index we have produced by analysing primary data constitutes a complementary source of useful information in order to understand short-term movements in the direct market more extensively. However, we do not have the information to distinguish between the plausible causes of a lack of relationship at the monthly level.

Appendix

Table A1: Geared and de-g geared monthly returns for indirect real estate indices.

	FTSE Real Estate Total Return	De-g geared FTSE RE Total Return		FTSE Real Estate Total Return	De-g geared FTSE RE Total Return		FTSE Real Estate Total Return	De-g geared FTSE RE Total Return
Jan-95	-4.7	-2.7	May-98	-6.8	-4.4	Sep-01	-9.9	-5.2
Feb-95	3.4	2.4	Jun-98	-4.7	-2.9	Oct-01	0.2	0.4
Mar-95	0.2	0.4	Jul-98	-10.3	-6.5	Nov-01	1.0	0.8
Apr-95	-2.9	-1.6	Aug-98	-3.8	-2.1	Dec-01	-1.5	-0.5
May-95	10.1	6.6	Sep-98	4.6	3.0	Jan-02	4.7	2.7
Jun-95	-1.1	-0.4	Oct-98	-6.5	-3.9	Feb-02	5.8	3.3
Jul-95	4.6	3.2	Nov-98	-0.1	0.2	Mar-02	1.8	1.2
Aug-95	-4.2	-2.5	Dec-98	-5.4	-3.1	Apr-02	7.1	4.1
Sep-95	1.0	0.9	Jan-99	-1.6	-0.7	May-02	2.8	1.7
Oct-95	-6.5	-3.8	Feb-99	10.7	6.3	Jun-02	-8.8	-4.5
Nov-95	4.2	2.9	Mar-99	2.4	1.6	Jul-02	-4.8	-2.2
Dec-95	3.2	2.2	Apr-99	4.0	2.6	Aug-02	-3.8	-1.8
Jan-96	1.3	1.1	May-99	4.9	3.2	Sep-02	-9.0	-4.7
Feb-96	-0.7	-0.2	Jun-99	-1.7	-0.8	Oct-02	6.4	3.5
Mar-96	0.9	0.8	Jul-99	1.1	0.9	Nov-02	-1.2	-0.4
Apr-96	9.5	6.0	Aug-99	1.1	0.9	Dec-02	-1.0	-0.2
May-96	-2.7	-1.4	Sep-99	-5.9	-3.5	Jan-03	-8.2	-3.6
Jun-96	-0.5	0.0	Oct-99	-6.1	-3.4	Feb-03	3.4	2.0
Jul-96	2.6	1.9	Nov-99	3.3	2.2	Mar-03	-6.4	-2.8
Aug-96	6.8	4.4	Dec-99	-3.2	-1.6	Apr-03	3.4	1.9
Sep-96	0.6	0.6	Jan-00	-6.8	-3.8	May-03	12.7	6.7
Oct-96	0.0	0.3	Feb-00	-7.8	-4.2	Jun-03	2.3	1.3
Nov-96	3.8	2.6	Mar-00	12.7	7.3	Jul-03	4.2	2.3
Dec-96	4.7	3.2	Apr-00	2.5	1.7	Aug-03	3.0	1.7
Jan-97	2.0	1.5	May-00	1.3	1.0	Sep-03	-0.5	0.1
Feb-97	4.1	2.8	Jun-00	6.4	3.9	Oct-03	3.3	1.8
Mar-97	-1.2	-0.5	Jul-00	3.8	2.4	Nov-03	6.1	3.1
Apr-97	4.3	3.1	Aug-00	5.2	3.3	Dec-03	4.3	2.3
May-97	8.5	5.8	Sep-00	-0.1	0.2	Jan-04	-1.1	-0.2
Jun-97	-5.3	-3.4	Oct-00	-4.3	-2.3	Feb-04	9.1	4.6
Jul-97	5.4	3.8	Nov-00	7.2	4.4	Mar-04	1.5	1.0
Aug-97	-3.0	-1.8	Dec-00	0.5	0.5	Apr-04	-0.8	-0.1
Sep-97	7.6	5.3	Jan-01	5.1	3.2	May-04	2.5	1.5
Oct-97	2.1	1.6	Feb-01	-0.6	-0.1	Jun-04	3.2	1.8
Nov-97	-1.8	-1.0	Mar-01	-2.1	-1.0	Jul-04	1.7	1.1
Dec-97	0.5	0.6	Apr-01	1.7	1.2	Aug-04	2.5	1.5
Jan-98	13.0	8.8	May-01	1.2	0.9	Sep-04	2.0	1.2
Feb-98	1.9	1.5	Jun-01	-1.8	-0.8	Oct-04	0.4	0.5
Mar-98	-1.0	-0.5	Jul-01	-0.5	0.0	Nov-04	7.0	3.7
Apr-98	0.0	0.2	Aug-01	0.9	0.7	Dec-04	10.2	5.4

Proof of equation (3)

If we start from the balance sheet identity which equates total assets and total liabilities we can also assume that the identity holds when we consider returns rather than total values:

$$r_{pt} * \frac{P_t}{E_t + D_t} + r_{at} * \frac{A_t}{E_t + D_t} = r_{et} * \frac{E_t}{E_t + D_t} + r_{dt} * \frac{D_t}{E_t + D_t}$$

If we isolate equity returns, we obtain the following equation:

$$r_{et} * \frac{E_t}{E_t + D_t} = r_{pt} * \frac{P_t}{E_t + D_t} + r_{at} * \frac{A_t}{E_t + D_t} - r_{dt} * \frac{D_t}{E_t + D_t}$$

We then multiply both sides by $\frac{E_t + D_t}{E_t}$ and obtain the following equation:

$$r_{et} = r_{pt} * \frac{P_t}{E_t} + r_{at} * \frac{A_t}{E_t} - r_{dt} * \frac{D_t}{E_t}$$

If we then assume $r_{at} = r_{dt}$, we obtain:

$$r_{et} = r_{pt} * \frac{P_t}{E_t} + r_{dt} * \left[\frac{A_t - D_t}{E_t} \right]$$

Since $A_t - D_t = E_t - P_t$, if we rearrange the previous equation, we obtain:

$$r_{pt} = \frac{r_{et} - r_{dt} * \left[1 - \frac{P_t}{E_t} \right]}{\frac{P_t}{E_t}}$$

which yields equation (3).

Chapter 4

CAPM, LIQUIDITY AND REAL ESTATE PERFORMANCE

4.1 INTRODUCTION

In the previous chapter, we employed a WACC model to retrieve private real estate returns from securitised ones. That model adjusted securitised real estate returns for gearing in order to reflect the same type of performance normally measured by valuation-based indices. This chapter proposes a model to adjust real estate stock returns for both leverage and liquidity effects at the same time. Instead of applying a WACC model (e.g. Barkham and Geltner [1995], Stevenson [2001], White and Holman [2002], Booth and Marcato [2004b]), we work within a CAPM framework (see Saunders and Ward [1978] and Sagalyn [1990]). In this area, the finance literature has recently developed new both theoretical and empirical evidences supporting the view that illiquidity affects asset returns. Particularly, Acharya and Pedersen [2005] demonstrate that liquidity predicts future returns (Jones [2001], Amihud [2002]), investors ask for an illiquidity premium (Chordia et al [2000, 2001]) and they are ready to pay a premium for highly performing securities in illiquid markets (Pastor and Stambaugh [2001]) and for liquid stocks when the market is down (Chordia et al [2000]). These findings would then strongly support the decision to include this factor in our CAPM model. We also find empirical evidence about the significance of these liquidity factors in real estate markets.

In this chapter we reach three main theoretical findings about the relationship between values of levered and unlevered companies when returns are net of illiquidity costs.

Firstly, the relationship between levered and unlevered beta – Rubenstein (1973) – is no more valid if we introduce illiquidity costs of equity markets and they are different from zero. To finance business activities through equity issues becomes expensive as shareholders will ask for an illiquidity premium to compensate for the risk they bear. This risk premium will then be reflected into the systematic risk, whose estimation will be biased. However, the Rubenstein's formula holds if illiquidity costs in both equity and debt markets are introduced and are equal. Their impacts will in fact cancel each other out. In this second case, shareholders do not prefer any type of form of financing because this does not create any value, all other conditions being equal. Thirdly, when illiquidity costs of debt exceed the ones of equity, the tax shield (obtained by increasing the leverage ratio) decreases along with the difference in value between a levered and unlevered company. In this case in fact it will be convenient to raise equity instead of debt. Finally, we propose and test the application of a Capital Asset Pricing Model (i.e. CAPM) net of illiquidity costs to obtain a proxy for direct real estate performances. We find this new index mathematically implying a lower volatility than the one shown by the original vehicle-based index. Our analysis also gives empirical evidence to this proposition.

The chapter is organised as follows: section 4.2 presents theoretical findings; section 4.3 shows the model to retrieve a series of direct property returns from a vehicle-based index; section 4.4 focuses on data and methodology used to adjust unsecuritised and securitised returns and to compare the two; finally, section 4.5 contains main results and section 4.6 draws main conclusions.

4.2 CAPM, LIQUIDITY AND LEVERAGE

Under the assumption of efficient capital markets, the Capital Asset Pricing Model states that asset returns are driven by the covariance between these returns and market ones, and the market risk premium:

$$E(r_i) = E(R_f) + \beta_i [E(r_M - R_f)] \quad (1)$$

where $E(r_i)$ and $E(r_M)$ are respectively expected asset and market returns, $E(R_f)$ represents the risk free rate, and β_i is the quantity of systematic risk computed as

$$\text{follows: } \beta_i = \frac{\text{Cov}(r_i, r_M)}{\sigma^2(r_M)}.$$

The relationship between security and market returns still holds even if net instead of gross returns are used (see Acharya and Pedersen [2005]):

$$E(r_i) = E(R_f + c_i) + \beta_i [E(r_M - c_M - R_f)] \quad (2)$$

where c_i and c_m are illiquidity costs of the asset and the entire market, and

$$\beta_i = \frac{\text{Cov}(r_i - c_i, r_M - c_M)}{\sigma^2(r_M - c_M)} \text{ represents the systematic risk.}$$

This version of the model can be re-written as follows:

$$E(r_i) = E(R_f + c_i) + \lambda \text{Cov}(r_i - c_i, r_M - c_M) \quad (3)$$

and thus by simply using properties of expected values:

$$E(r_i) = E(R_f + c_i) + \lambda \text{Cov}(r_i, r_M) + \lambda \text{Cov}(c_i, c_M) - \lambda \text{Cov}(r_i, c_M) - \lambda \text{Cov}(c_i, r_M) \quad (4)$$

$$\text{where } \lambda = \frac{[E(r_M - c_M - R_f)]}{\sigma^2(r_M - c_M)}.$$

Acharya and Pedersen both theoretically and empirically prove that asset returns are driven not only by systematic risk, but also by three different liquidity premiums investors require or may pay. Equation 4 is preferable to equation 3 because it highlights these three main factors. Firstly a commonality in liquidity exists and investors ask for an excess return for illiquid assets traded in illiquid markets (i.e. $\text{Cov}(c_i, c_M)$ factor). Secondly, investors are willing to pay a premium for a security showing high return if the market is illiquid (i.e. $\text{Cov}(r_i, c_M)$ factor). Finally, investors are willing to pay a premium to hold a liquid security when markets are falling (i.e. $\text{Cov}(c_i, r_M)$ factor).

As the CAPM formula is valid for any security (or portfolio of securities, e.g. indices), we can derive the same relationship for debt markets (with $E(r_d)$ being the expected return of debt), both with gross (equation 5) and net (equation 6) returns:

$$E(r_d) = E(R_f) + \lambda \text{Cov}(r_d, r_M - c_M) \quad (5)$$

$$E(r_d) = E(R_f + c_d) + \lambda \text{Cov}(r_d - c_d, r_M - c_M) \quad (6)$$

In order to remove the effect of debt from property stock returns, we need to retrieve the relationship between performances of a levered and unlevered company. When gross returns are used, the CAPM of an unlevered company (from this point onwards referred to by using the sign *) can be expressed as follows:

$$E(r_i)^* = E(R_f) + \beta_i^* [E(r_M) - R_f] \quad (7)$$

The β^* factor of a unlevered company is linked with the β factor of the same but levered company and its debt-to-equity ratio through the Rubenstein (1973)'s formula:

$$\beta^* = \beta \frac{S}{S + D(1 - t)} \quad (8)$$

where S and D represent the market values of respectively shares and debt of the company, and t is the corporation tax.

However, when we introduce illiquidity costs this relationship holds only under specific conditions. We present some theoretical propositions analysing the impact of debt and illiquidity costs on returns of levered and unlevered companies.

Proposition 1 *Suppose $c_i > 0$ and $c_d = 0$. Then $V^* \neq V - tD$ and $\beta^* \neq \beta \frac{S}{S + D(1-t)}$.*

We start from a simple world where illiquidity costs exist only in equity markets (and not in debt markets). The Rubenstein's formula does not hold anymore. So, the tax shield the model yields is different from tD . The only opportunity for the formula to hold is when $c_i = 0$, but this is not verifying the initial condition in the proposition.

However, if we introduce illiquidity costs in both equity and debt markets, we obtain a representation of the world which is more similar to the real one. In this case, we see that even if the two illiquidity costs are different from zero equation 8 holds.

Proposition 2 *Suppose $c_i > 0$, $c_d > 0$. Then $V^* = V - tD$ and $\beta^* = \beta \frac{S}{S + D(1-t)}$ if and only if $c_i = c_d$.*

This is to say that in order to have the same relationship between levered and unlevered values we need to assume that the costs of illiquidity are equal in equity and bond markets. In other words, if the company issues debt tradable on the market, the liquidity

premiums of equity and debt instruments required by investors are equal. This assumption is not far from reality, at least in relative terms. In fact, the riskier the company (or market), the higher the liquidity premium in share prices, the lower the rating of its corporate bonds and then probably the higher the liquidity premium of its debt. The model we develop starts from this assumption.

Proposition 3 *Suppose $c_i > 0$, $c_d > 0$ and $c_i < c_d$. Then $\frac{\partial V^*}{\partial t}$ decreases.*

This finding demonstrates the general intuition under which if illiquidity costs are lower in equity than in bond markets, the tax shield a levered company may benefit from is lower than in the case of illiquidity costs equal in the two markets. This is because the advantage of debt interest deductions are reduced by costs linked with the illiquidity of the financing instrument. For this reason it is important to analyse the relationship between levels of liquidity and taxation between different markets.

4.3 THE CAPM FRAMEWORK

Our model is developed in a CAPM framework considering net returns. So, illiquidity costs are subtracted from gross returns in order to measure net returns of an investor. Finally, illiquidity costs are supposed to be equal in all markets (e.g. equity and bond).

If equation 2 represents expected levered returns net of illiquidity costs, expected net unlevered returns are expressed as follows:

$$E(r_i)^* = E(R_f + c_i) + \beta_i^* [E(r_M - c_M - R_f)] \quad (9)$$

Hence, by substituting $[E(r_M - c_M - R_f)]$ from equation 2 into equation 9, we obtain:

$$E(r_i)^* = E(R_f + c_i) + \frac{\beta_i^*}{\beta_i} [E(r_i - c_i - R_f)] \quad (10)$$

Equation 10 represents our model to retrieve direct property performance from vehicle-based indices. This model states that the expected return of investments in private real estate is given by a minimum rate plus illiquidity costs plus a real estate premium (net of illiquidity costs) over the risk free rate adjusted by leverage $\left(\frac{\beta_i^*}{\beta_i}\right)$.

Proposition 4 *When either $E(r_i) > 0$ and $E(r_i) > E(R_f + c_i)$, or $E(r_i) < 0$, then*
 $|E(r_i)^*| < |E(r_i)|$.

This model produces a smoother series than the original securitised one because unlevered returns are – in absolute values – lower than original ones if we exclude all

returns included in the range between zero and the risk free rate plus illiquidity costs. On one hand, when levered returns are lower than zero, the relationship $E(r_i)^* > E(r_i)$ holds. On the other hand, if they are higher than the risk free rate gross of illiquidity costs, unlevered returns are lower than levered ones. This finding implies a lower volatility for adjusted securitised returns than for original ones, which is a result we would expect. If we introduce or increase the level of leverage, investors perceive a higher risk and then require a higher return.

4.4 ILLIQUIDITY RISK MEASURES

If theoretically our model shows interesting properties (e.g. it deals with liquidity and gearing at the same time, it obtains a lower volatility for adjusted returns than for original returns), its empirical application faces some key issues. In particular, as there is a lack of an exact measure of illiquidity, we are aware of the need to use a proxy, which may represent the theoretical factor included in our model. Some proxies used in the finance literature (e.g. bid-ask spread) are based on microstructure data (i.e. intraday trading) and are not available for long time series in any financial market and mostly when they are needed to retrieve an annual direct property index. We then suggest three plausible ratios to use within an empirical analysis. They represent either a measure of the sensitivity of returns (r_i) to transaction volumes ($trans_i$), or the frequency of transactions, or a combination of the two.

The first proxy is taken from Acharya and Pedersen [2005], who modify an earlier measure developed by Amihud [2002].

Their illiquidity ratio shows the sensitivity of returns to transaction volumes:

$$illiq_t = \left[\frac{1}{days_t} \sum_{i=1}^n \frac{abs(r_i)}{trans_i} \right]$$

A simple absolute returns / transaction volumes ratio would not be stationary as transaction volumes (expressed in value terms) tend to increase over time because of inflation. This ratio is then multiplied by an adjustment factor, i.e. the quotient between the market value at time t and the one at time 0. The illiquidity risk is finally multiplied by a factor of 10^6 .

For equity markets, we define a normalised measure in order to obtain same statistical properties found by Chalmers and Kadlec [1998] and Acharya and Pedersen in the

finance literature: $0.25 + 0.3 * illiq_t * \frac{MV_t}{MV_0}$. The illiquidity cost ranges between 0.55%

and 2.60% (vs. 0.25% and 4.16%) with an average of 1.43% (vs. 1.11%) for equities,

and between 0.52% and 2.29% with an average of 1.19% for real estate. Standard deviations are respectively equal to 0.61% (vs. 0.37%) and 0.39%.

A second measure is computed as the inverse of the turnover ratio, computed as volume of transactions over average capital employed throughout the year (amv_i)²⁸:

$$illiq_i = \frac{1}{\frac{trans_i}{amv_i}}$$

This measure is very simple and shows the turnover of a specific asset. If monthly transactions are one fourth of the average market value in each month, it means that the index portfolio is rotating every four months. This second measure of illiquidity costs is normalized by multiplying it by a factor of 10^2 and dividing it by 2. The average illiquidity cost for equities and real estate markets are respectively equal to 1.02% and 1.30%, with standard deviations equal to 0.46% and 0.30%.

However, this quotient does not consider how different turnover ratios may influence prices. We then propose a new ratio by combining the two previous measures:

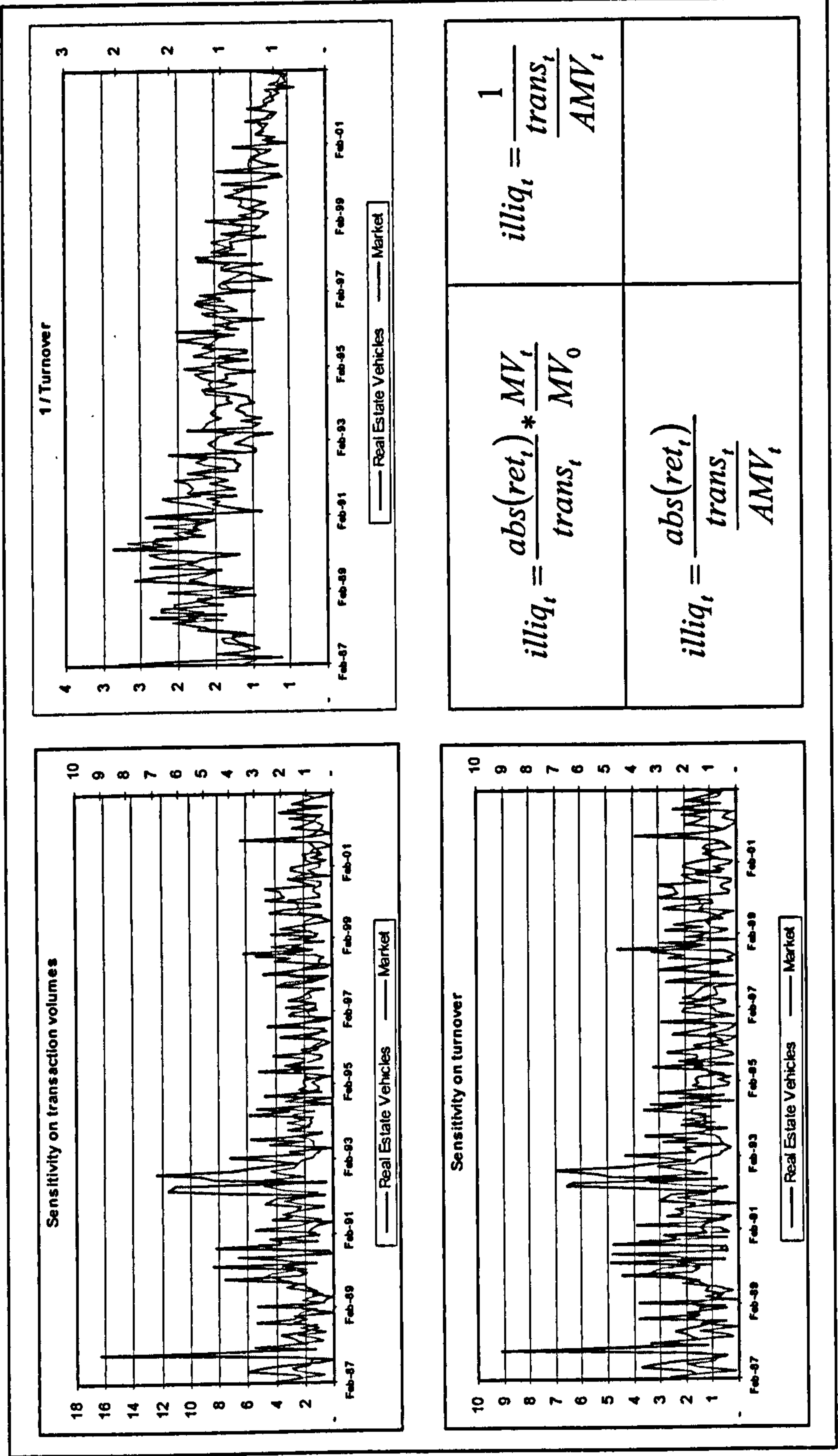
$$illiq_i = \left[\frac{1}{days_i} \sum_{i=1}^n \frac{abs(r_i)}{\frac{trans_i}{amv_i}} \right]$$

²⁸ The turnover rate (unless inverted) would represent a measure of liquidity rather than illiquidity.

It shows the sensitivity of returns to turnover rates and, being a combination of the previous ratios, we prefer it to the other two. Following Acharya and Pedersen's procedure, the illiquidity risk is finally multiplied by a factor of 10^3 and normalised in order to obtain same statistical properties found in the finance literature: $0.25 + 0.3 * illiq_t$. The illiquidity cost ranges between 0.73% and 1.30% with an average of 1.01% for equities and between 0.83% and 5.34% with an average of 2.47% for real estate shares. Standard deviations are respectively equal to 0.16% and 1.08%.

We think that these results (higher illiquidity costs in the real estate sector), along with a more intuitive interpretation of our measure (sensitivity to turnover rates rather than turnover volumes), suggest a preference for our measure. However, we also recognise that the first and third measures can be read in a similar way (with the one from Acharya and Pedersen multiplying our own measure by the initial market value). Consequently, both measures will be used in our analysis and conclusions will be drawn upon empirical results. Finally we find a higher standard deviation than in previous studies, but the two measures refer to a different feature. Our standard deviation is computed on a time series basis, while the one calculated by Acharya and Pedersen refers to a cross-sectional framework.

Graph 4.1: The three illiquidity cost measures



Graph 4.1 shows the pattern of the three illiquidity measures²⁹. Firstly, sensitivity to transaction volumes and sensitivity to turnover ratio are both stationary and signalling periods of crisis in both real estate (late 1980s and early 1990s) and equity markets (1987 and 1998). Secondly, the inverse of transactions turnover is non stationary and has two clear trends (a positive one at the beginning of the period and a negative one starting in early 1990s). Since the second measure also shows a constant standard deviation without signalling periods of higher volatility (i.e. illiquid markets), we believe it does not represent an adequate proxy for illiquidity costs. However, we do not have a strong a-priori to choose between the other two measures. We then decide to use both proxies in our empirical analysis. Results will then suggest which proxy is to be preferred.

4.5 DATA AND METHODOLOGY

The indices used for annual and monthly analysis respectively are:

- IPD Annual index and Datastream Real Estate Sector index (from 1987 to 2004).
- IPD Monthly index and Datastream Real Estate Sector index (from January 1995 to December 2004).

²⁹ Graphs do not show illiquidity costs, but *illiq* measures before they are normalised.

In this chapter we decided to use the Datastream Real Estate Sector index (as opposed to the FTSE 350 Real Estate Sector index) because we need to obtain transaction volumes at the index level to compute illiquidity costs and they are only available for Datastream indices. We thus think that using the same source of information for returns and transaction volumes gives consistency to the application of the CAPM methodology. The leverage ratio for the annual analysis was directly obtained from Datastream, the main rationale being the consistency of the dataset. The choice to start the annual analysis only from 1987 is due to a lack of transaction volumes data in earlier periods. For Datastream indices in fact daily transaction volumes start at the end of October 1986. The leverage ratio for the monthly study is the ratio we computed in the previous chapter using market values and information from primary sources. However, we also compute a monthly series based only on book values for both equity and debt. Indices created with this second leverage ratio include the suffix “2” in their label. The availability of data limited our monthly empirical analysis to the period starting in January 1995 and ending in December 2004.

We initially test for the sensitivity of real estate share prices to equity returns and illiquidity risks of both real estate and equity markets. As we assume market efficiency in at least a weak form and expected values should then be incorporated in real estate prices, we compute innovations for illiquidity costs and market returns. We apply a simple autoregressive process of order two and use residuals as a proxy for innovations.

The measure of illiquidity used in this model is sensitivity to turnover (i.e. third one).

We specify the following model:

$$E(r_{RE_t}) = \alpha_t + \beta * I(E(r_{EQ_t})) + \sum_{i=0}^{12} \delta_i * I(ill_{RE_{t-i}}) + \lambda * I(ill_{EQ_t}) + \varepsilon_t$$

where $E(r_{RE_t})$ represents the expected real estate return, $I(E(r_{EQ_t}))$, $I(ill_{RE_{t-i}})$ and $I(ill_{EQ_t})$ respectively refer to innovations in equity returns, illiquidity costs for real estate and equity markets, and β , δ_i and λ are their coefficients.

Table 4.1 shows ten different models considering illiquidity and market factors. Results show that real estate returns are sensitive to both innovations in illiquidity and unexpected market returns. Particularly, unexpected market returns (i.e. innovations in market returns) are significant at a 99% level. The adjusted R-squared ranges between 0.39 and 0.49 for models including market returns, and the Durbin-Watson statistic shows no significant autocorrelation pattern in error terms. Furthermore, all coefficients show a sign that is economically plausible and consistent with previous literature. Specifically, we find a positive relationship between unexpected equity returns and real estate ones, which implies the existence of a positive beta. This beta is also less than 1 and suggests real estate shares are “conservative” assets. Secondly, investors require an illiquidity risk premium as real estate returns increase when both current and lagged illiquidity costs in real estate markets increase.

Table 4.1: Testing the significance of illiquidity costs in explaining real estate returns

Regression	α	β	δ_0	δ_2	δ_7	δ_{11}	λ	Adjusted R-squared	D-W stats
1	0.65** 2.06	0.78*** 11.88	0.29** 2.02					0.47	1.89
2	0.57* 1.81	0.80*** 12.71		0.24* 1.77				0.48	1.95
3	0.48* 1.52	0.79*** 12.78			0.30** 2.26			0.48	1.97
4	0.46* 1.46	0.70*** 10.05				0.37** 2.77		0.39	1.98
5	0.46* 1.48	0.70*** 10.04			0.22* 1.58	0.32** 2.33		0.39	2.00
6	0.65** 2.06	0.79*** 12.34					-1.06** -2.01	0.48	1.90
7	0.57* 1.82	0.77*** 12.11					-1.01* -1.93	0.48	1.97
8	0.48* 1.54	0.76*** 12.10					-1.15** -2.24	0.49	2.02
9	0.43 1.38	0.70*** 10.13					-0.98* -1.70	0.39	2.04
10	0.39 0.87		0.71** 3.54	0.36** 2.07	0.32* 1.84		-1.07* -1.46	0.15	1.91

We estimate the following model under ten different specifications: $E(r_{RE,t}) = \alpha_t + \beta * I(E(r_{EQ,t})) + \sum_{i=0}^{12} \delta_i * I(ill_{RE,t-i}) + \lambda * I(ill_{EQ,t}) + \varepsilon_t$. Each specification

assumes some of the coefficients to be null. The β coefficient represents the single factor, which is normally used in a CAPM framework to estimate the systematic risk of an asset. Coefficients δ_0 , δ_2 , δ_7 and δ_{11} represent the sensitivity of real estate returns to innovations in the real estate sector illiquidity, respectively with no, two month, seven month and eleven month lag. Finally, the coefficient λ indicates the sensitivity of real estate returns to innovations in equity market illiquidity. Innovations are computed, for each variable, from the residuals of an autoregressive process of order 2.

Thirdly, investors look at real estate securities as an illiquidity hedging asset, i.e. a less risky asset than other types of equities. They are consequently willing to pay a premium to hold real estate securities when equity markets are highly illiquid. This is due to the fact that real estate shares behave as stocks (see real estate literature on integration of financial markets), but the correlation between real estate shares and illiquidity in equity markets is equal to -0.23 (see finance literature on liquidity), and the commonality in liquidity is lower than for other types of stocks (0.5 vs. 0.8-0.9).

Finally, the tenth equation shows that just illiquidity itself is explaining 15% of total return variations and so it does matter when we model real estate market returns. We then conclude that illiquidity is an important factor and we include it when we apply our CAPM model to retrieve direct real estate performances.

4.5.1 Adjustments of returns in direct real estate

On one hand real estate vehicles show levered returns that need to be adjusted. However, on the other hand private real estate market information embodies a feature induced by valuation data. Real estate indices measuring the return of direct investment in fact, suffer from smoothing that results in a lower volatility.

In order to adjust these returns, we use the unsmoothing procedure suggested by Fisher-Geltner-Webb [1994], i.e. first-order autoregressive reverse filter (foarf). Unsmoothed capital growth rates for direct real estate investment (i.e. ucg_t) are computed with the same procedure described in section 3.2.2.1 (page 102).

4.5.2 Adjustments of returns in real estate shares

We proceed to extrapolate a direct performance from equation (10) with two different procedures for annual and monthly frequencies.

If annual figures are used, the available time period does not allow us to apply a time varying β parameter and this is then computed as a fixed parameter throughout the period by simply regressing the net market risk premium [i.e. $NMP = \text{market return} - \text{risk free rate} - \text{market illiquidity costs}$] on the net real estate premium [i.e. $NREP = \text{Real estate return} - \text{risk free rate} - \text{real estate illiquidity costs}$]. Instead, when we use a monthly frequency, the length of the time series allows us to compute a time-varying β parameter by regressing – on a basis of 30, 60 and 90 rolling days – the NMP on the NREP.

For both frequencies the parameter β^* is subsequently obtained from the estimated β , the main corporation tax rate³⁰ and the leverage ratio by applying equation (8). The risk free rate and illiquidity costs are known. Expected net real estate premiums are computed from the two estimated coefficients α and β .

We compute two sets of indices by using our measure of illiquidity costs and the one suggested by Acharya and Pedersen.

We also compute another adjusted index for real estate shares by applying the WACC (weighted average cost of capital) methodology used in Booth and Marcato [2004b].

³⁰ Source: Inland Revenue. Monthly rates are assumed to be constant throughout the year and changing only at the beginning of the year when the government intervenes.

4.5.3 Index comparison

We compare both the original and the unsmoothed valuation-based index with the Datastream Real Estate Sector index and several CAPM-adjusted Datastream indices, following the main steps described in 3.2.3 to analyse:

- cyclical patterns (i.e. peaks, uprising and down-falling phases);
- descriptive statistics³¹ and deviations from normality³²;
- contemporaneous and inter-temporal dependency between (both original and adjusted) securitised and unsecuritised real estate returns³³;
- causality effects between direct and indirect property performances³⁴.

³¹ E.g. mean, median, standard deviation, kurtosis, skewness and autocorrelation function.

³² Additionally to the Jarque-Bera test, we compute the *Lilliefors statistic* – a modified version of the Kolmorov-Smirnov goodness-of-fit statistic. It is very intuitive and it tests for normality when the population parameters are unknown. After ranking data values from the smallest to the largest one (x_1, x_2, \dots, x_n), the average (μ) and variance (σ^2) of the unbiased sample estimators are used to standardize data values. If $\Phi(z)$ denotes the standard normal cumulative distribution function and the empirical distribution function (i.e. EDF) of the data for every z is computed as $F_n(z) = \frac{\text{number of } z_{(i)}'s \leq z}{n}$, the

Lilliefors test statistics – with a p-value computed from the Dallal-Wilkinson (1986) formula – represents the maximum vertical distance between $F_n(z)$ and $\Phi(z)$: $L = \max\{F_n(z) - \Phi(z), -\infty \leq z \leq \infty\}$.

³³ Pearson's correlation coefficient, Kendall's Tau and Spearman's Rho.

³⁴ Granger causality test.

4.6 RESULTS

Tables 4.2 and 4.3 contain labels and definitions for all indexes we use in our analysis respectively for the annual and monthly analysis. Along with original series and an unsmoothed version of IPD returns, we obtain a series of adjusted real estate shares indexes with modified versions of the same model. Particularly, for the annual frequency we create one WACC and two CAPM-adjusted series, while for the monthly frequency we obtain two WACC and twelve CAPM-adjusted indexes.

Table 4.2: Label and description of return series

Label	Description
ipd	Investment Property Databank valuation-based index
foarf	Unsmoothed IPD index using a first order autoregressive function
ftse re	Datastream real estate sector index
wacc	Indirect real estate index adjusted with a WACC model
capm	Indirect real estate index adjusted with a CAPM model and M's illiquidity costs
capm-ap	Indirect real estate index adjusted with a CAPM model and AP's illiquidity costs

Table 4.3: Label and description of monthly return series

Label	Description
ipd	Investment Property Databank valuation-based index
foarf	Unsmoothed IPD index using a first order autoregressive function
ftse	Datastream real estate sector index
wacc	Indirect real estate index adjusted with a WACC model (gearing with market values)
wacc2	Indirect real estate index adjusted with a WACC model (gearing with book values)
capm90	Indirect real estate index adjusted with a CAPM model, M's illiquidity costs and 90 rolling days (gearing with market values)
capm60	Indirect real estate index adjusted with a CAPM model, M's illiquidity costs and 60 rolling days (gearing with market values)
capm30	Indirect real estate index adjusted with a CAPM model, M's illiquidity costs and 30 rolling days (gearing with market values)
capm90_2	Indirect real estate index adjusted with a CAPM model, M's illiquidity costs and 90 rolling days (gearing with book values)
capm60_2	Indirect real estate index adjusted with a CAPM model, M's illiquidity costs and 60 rolling days (gearing with book values)
capm30_2	Indirect real estate index adjusted with a CAPM model, M's illiquidity costs and 30 rolling days (gearing with book values)
capm90-ap	Indirect real estate index adjusted with a CAPM model, AP's illiquidity costs and 90 rolling days (gearing with market values)
capm60-ap	Indirect real estate index adjusted with a CAPM model, AP's illiquidity costs and 60 rolling days (gearing with market values)
capm30-ap	Indirect real estate index adjusted with a CAPM model, AP's illiquidity costs and 30 rolling days (gearing with market values)
capm90-ap2	Indirect real estate index adjusted with a CAPM model, AP's illiquidity costs and 90 rolling days (gearing with book values)
capm60-ap2	Indirect real estate index adjusted with a CAPM model, AP's illiquidity costs and 60 rolling days (gearing with book values)
capm30-ap2	Indirect real estate index adjusted with a CAPM model, AP's illiquidity costs and 30 rolling days (gearing with book values)

4.6.1 Annual returns

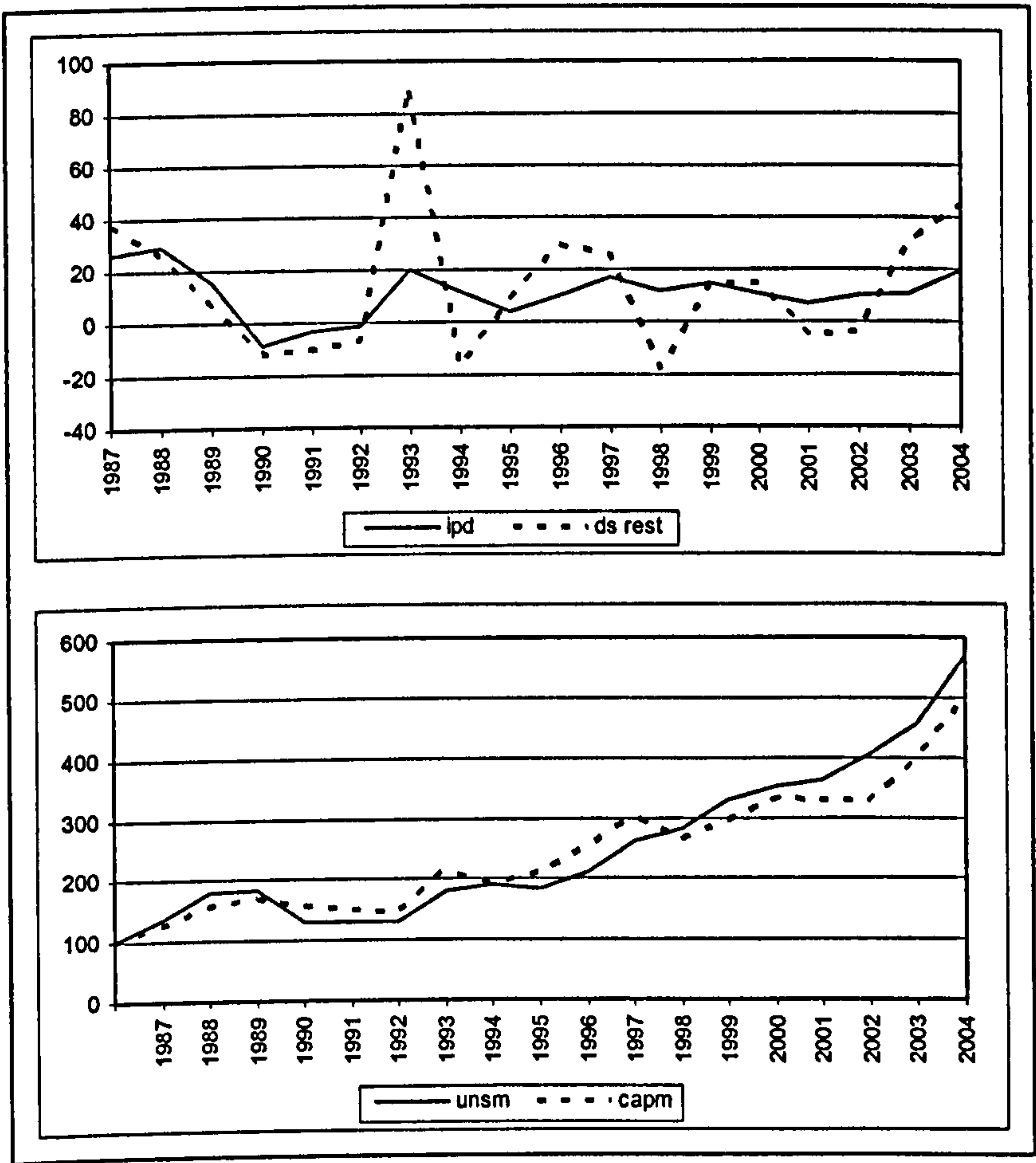
Table 4.4 reports main descriptive statistics. The average return for both IPD and unsmoothed indices is equal to 11.3%, with a standard deviation that is respectively equal to 9.7% and 16.2%. Real estate shares show a higher average return (14.2%) with a much higher standard deviation (27.2%). When this index is adjusted, we obtain a lower average return (respectively 10.3%, 9.7% and 11.1% for CAPM adjusted, CAPM adjusted with AP measure of liquidity and WACC model) and a lower risk (around 15%). This empirical finding supports our fourth proposition.

Skewness and Kurtosis also show similar values to the ones of a normal distribution. In fact we cannot reject normality with either Jarque-Bera or Lilliefors tests for any of the indices.

Table 4.4: Descriptive statistics of annual returns

	Mean	Standard Deviation	Return per unit of risk	Skewness	Kurtosis	Jarque-Bera	Lilliefors
lpd	11.31	9.71	1.17	-0.18	2.79	0.279	0.155
unsm	11.33	16.16	0.70	-0.38	3.58	0.390	0.129
ds rest	14.16	27.18	0.52	1.12	4.32	3.706	0.132
wacc	11.11	15.65	0.71	0.86	3.47	1.886	0.146
capm	10.31	15.08	0.68	0.37	2.45	0.852	0.134
capm-ap	9.70	15.08	0.64	0.39	2.48	0.852	0.136
Critical value					10%	4.605	0.184
					5%	5.992	0.200
					1%	9.210	0.239

Graph 4.2: Original and adjusted annual returns



Graph 4.2 shows the cyclical behaviour of original and adjusted annual performances. If we exclude 1990 when there is a significant difference, unsmoothed IPD returns and CAPM-adjusted Datastream returns (i.e. graph below) behave much more similarly than original IPD and Datastream indices. We believe this result is due to two main factors: a fall in direct real estate prices (which is bigger for unsmoothed than for original IPD returns), and a problem arising from the application of the methodology to an annual

frequency. In fact, since the number of observations is too small to justify the application of a rolling methodology for the estimation of beta, we decided to estimate a fixed beta for the entire period. However, in a rolling structure, our estimated beta would only refer to the last year beta (and it is probably similar to a few of the previous beta. its value would be different from the one estimated during earlier years.

Table 4.5: Dependency measures for contemporaneous relationship (annual)

	Pearson		Kendall		Spearman	
	lpd	unsm	lpd	unsm	lpd	unsm
lpd	1.00	0.89	1.00	0.66	1.00	0.85
unsm	0.89	1.00	0.66	1.00	0.85	1.00
ds rest	0.61	0.75	0.49	0.54	0.62	0.75
wacc	0.66	0.79	0.52	0.59	0.66	0.78
capm	0.67	0.78	0.53	0.61	0.67	0.79
capm-ap	0.67	0.78	0.53	0.61	0.67	0.79

All coefficients are significantly different from zero.

The existence of a closer relationship between adjusted returns than original time series is also confirmed by their dependency measures. Table 4.5 shows matrices of Pearson’s correlation coefficient, Kendall’s Tau and Spearman’s Rho between adjusted securitised returns and private real estate indices (either smoothed or unsmoothed). All three measures suggest an improvement if we adjust both IPD and Datastream indexes. Coefficients for raw returns are respectively equal to 0.61, 0.49 and 0.62, while coefficients for adjusted performances are 0.78, 0.61 and 0.79. Differently from Booth

and Marcato [2004b], we also find that adjustments made to real estate shares do improve dependency with the original IPD series (respectively reaching 0.67, 0.53 and 0.67). Finally, in line with previous literature, we obtain a higher dependency when we unsmooth the IPD index (dependency figures with the Datastream real estate sector index increase to 0.75, 0.54 and 0.75).

Table 4.6: Inter-temporal dependency measures of securitised returns with valuation-based indices (annual)

Panel A: IPD indices

	Pearson				Kendall				Spearman			
	ds rest	wacc	capm	capm-ap	ds rest	wacc	capm	capm-ap	ds rest	wacc	capm	capm-ap
Lag +3	-0.40	-0.40	-0.34	-0.35	-0.16	-0.12	-0.14	-0.14	-0.17	-0.14	-0.15	-0.15
Lag +2	-0.29	-0.29	-0.24	-0.24	-0.20	-0.20	-0.18	-0.18	-0.22	-0.24	-0.21	-0.21
Lag +1	-0.19	-0.15	-0.12	-0.12	-0.19	-0.18	-0.16	-0.16	-0.26	-0.20	-0.19	-0.19
Lag 0	0.61	0.66	0.67	0.67	0.49	0.52	0.53	0.53	0.62	0.66	0.67	0.67
Lag -1	0.39	0.43	0.45	0.45	0.41	0.40	0.38	0.38	0.52	0.54	0.52	0.52
Lag -2	-0.19	-0.20	-0.20	-0.19	-0.07	-0.08	-0.10	-0.10	-0.06	-0.12	-0.12	-0.12
Lag -3	-0.28	-0.38	-0.40	-0.40	-0.28	-0.33	-0.31	-0.31	-0.35	-0.44	-0.41	-0.41

Panel B: Unsmoothed IPD indices

	Pearson				Kendall				Spearman			
	ds rest	wacc	capm	capm-ap	ds rest	wacc	capm	capm-ap	ds rest	wacc	capm	capm-ap
Lag +3	-0.45	-0.44	-0.37	-0.38	-0.03	-0.03	-0.01	-0.01	-0.02	-0.01	0.00	0.00
Lag +2	-0.11	-0.11	-0.08	-0.08	-0.08	-0.08	-0.07	-0.07	-0.11	-0.14	-0.11	-0.11
Lag +1	-0.06	-0.02	0.00	-0.01	-0.01	0.00	0.01	0.01	-0.08	-0.05	-0.04	-0.04
Lag 0	0.75	0.79	0.78	0.78	0.54	0.59	0.61	0.61	0.75	0.78	0.79	0.79
Lag -1	0.12	0.14	0.15	0.15	0.21	0.16	0.15	0.15	0.29	0.25	0.24	0.24
Lag -2	-0.39	-0.42	-0.42	-0.42	-0.22	-0.27	-0.25	-0.25	-0.29	-0.36	-0.35	-0.35
Lag -3	-0.22	-0.31	-0.34	-0.34	-0.07	-0.12	-0.10	-0.10	-0.14	-0.22	-0.18	-0.18

All coefficients are significantly different from zero.

Furthermore, we analyse the inter-temporal dependency between indirect real estate markets and direct ones (measured by either valuation-based indexes or an unsmoothed version of them). Table 4.6 shows the three measures of dependency with lags up to three in either direction. Positive (and negative) lags refer to direct real estate markets leading securitised markets (and viceversa). For all coefficients the highest figures are at lag zero (for any index) and the only other positive figure is at lag one, suggesting real estate shares (either raw or adjusted) lead private property markets.

The only difference we find between the inter-temporal dependency of indirect real estate returns with IPD and unsmoothed returns is, for all measures, a lower ratio at lag one (and a higher ratio at lag zero) for the latter.

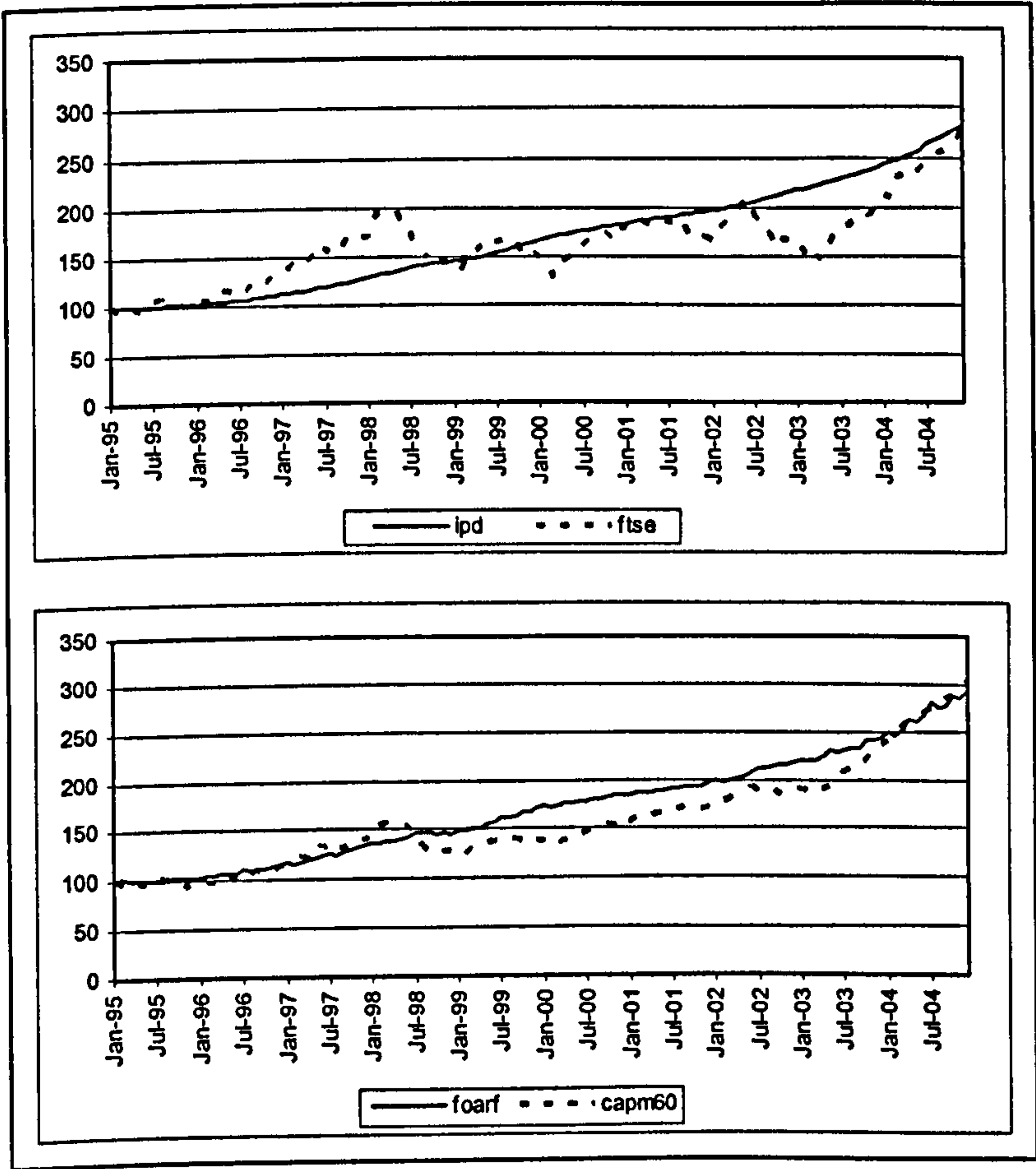
Table 4.7: Granger causality test (annual)

	1	2	3	4	5	6
1 ipd		5.41**	0.18	0.14	0.05	0.06
2 foarf	5.69**		0.15	0.20	0.22	0.22
3 ftse re	0.47	0.02		0.96	1.58	1.50
4 wacc	0.74	0.01	0.45		0.85	0.77
5 capm	0.85	0.00	0.70	0.51		0.51
6 capm-ap	0.86	0.00	0.69	0.47	0.58	

If we consider this matrix with only numbers (and excluding labels), we obtain a 6 by 6 matrix. Each cell in position (n,m) reports the F-statistic associated to the index in row n granger causing the index in column m. The opposite element (m,n) will contain the F-statistic associated to the index in row m granger causing the index in column n. As an example, 5.69 – cell (2,1) – represents the statistic of the test with null hypothesis “foarf does not granger cause ipd”. Likewise, 5.41 – cell (1,2) – represents the statistic of the test with null hypothesis “ipd does not granger cause foarf”. If both values are either significant or not significant, we cannot conclude that one variable granger causes the other one (as it happens in the example we chose). This conclusion can only be reached if one of the two F-statistic is significant and the other one is not.

However the value of contemporaneous dependency is always higher than the one of lagged dependency and consequently the existing lead/lag structure is not clear. Moreover, the granger causality test (up to one year lag) does not show any significant lead/lag structure between securitised and unsecuritised markets (see table 4.7). We think this is due to the frequency of returns and we expect a monthly frequency to shed its light upon this conclusion.

Graph 4.3: Original and adjusted monthly indices



4.6.2 Monthly returns

Graph 4.3 shows original and adjusted indexes. As an example, we only plot one version of our CAPM-adjusted series, the one using our measure of illiquidity, a leverage ratio computed with market values and sixty rolling days to estimate alpha and beta coefficients. Adjusted direct and indirect returns (graph below) clearly behave much more similarly than original ones. On one hand unsmoothed private real estate returns are more volatile than IPD ones. On the other hand, CAPM-adjusted real estate share prices are smoother than original ones.

Descriptive statistics are reported in table 4.8. The average return of direct real estate is respectively equal to 0.89% and 0.94% for the original and unsmoothed versions. Indexes adjusted with a WACC model are yielding a return / risk trade-off of 0.82 / 2.85 and 0.95 / 4.32 respectively for leverage computed with market and book values. When we use our CAPM model, average returns range between 0.68 (capm90) and 1.50 (capm30_2) with standard deviations ranging from 1.73% (capm30-ap2) and 2.83% (capm90). Consequently if we analyse the amount of return per unit of risk³⁵, original series show a significant difference (2.28 for direct vs. 0.22 for indirect indexes), which is reduced when we adjust raw data. Particularly our CAPM methodology yields better results (ratio between 0.24 and 0.80) than the WACC model (0.22 or 0.29), compared with unsmoothed IPD returns (0.73).

³⁵ The amount per unit of risk is computed as the ratio between average return and standard deviation.

Table 4.8: Descriptive statistics of monthly returns

	Mean	Standard Deviation	Return per unit of risk	Skewness	Kurtosis	Median	Jarque-Bera	Lilliefors
ipd	0.89	0.39	2.28	0.37	3.15	0.82	2.730	0.09**
unsm	0.94	1.30	0.73	0.35	3.09	0.76	2.466	0.071
ds rest	1.06	4.90	0.22	0.00	2.96	1.15	0.042	0.058
wacc	0.82	2.85	0.29	0.00	3.06	0.92	0.000	0.059
wacc2	0.95	4.32	0.22	-1.16	9.70	1.28	239.78***	0.094**
capm90	0.68	2.83	0.24	-0.46	3.81	1.12	6.943**	0.091**
capm60	1.01	2.69	0.37	-0.28	4.15	1.28	7.356**	0.087**
capm30	1.14	2.53	0.45	-0.20	4.32	1.22	8.486**	0.087**
capm90_2	1.17	2.16	0.54	-0.85	5.02	1.33	32.866***	0.064
capm60_2	1.42	1.92	0.74	-0.59	4.94	1.36	23.991***	0.081**
capm30_2	1.50	1.88	0.80	-0.26	4.25	1.47	8.264**	0.079*
capm90-ap	1.07	2.57	0.42	-0.31	4.18	1.55	8.067**	0.108***
capm60-ap	1.26	2.45	0.51	-0.07	4.59	1.55	11.54***	0.11***
capm30-ap	1.32	2.25	0.59	0.10	4.83	1.55	15.419***	0.131***
capm90-ap2	0.84	2.06	0.41	-0.94	5.51	1.13	46.693***	0.084**
capm60-ap2	1.05	1.83	0.58	-0.56	5.52	1.41	35.635***	0.085**
capm30-ap2	1.14	1.73	0.66	-0.19	5.00	1.29	19.038***	0.13***
				Critical value			10%	0.073
							5%	0.081
							1%	0.094

Table 4.9: Dependency measures for contemporaneous relationship (monthly)

	Pearson		Kendall		Spearman	
	lpd	unsm	lpd	unsm	lpd	unsm
lpd	1.00	0.60	1.00	0.40	1.00	0.54
unsm	0.60	1.00	0.40	1.00	0.54	1.00
ds rest	0.04	0.01	0.03	0.02	0.04	0.03
wacc	0.02	-0.01	0.02	0.01	0.02	0.02
wacc2	-0.12	-0.03	-0.09	-0.04	-0.14	-0.05
capm90	0.07	-0.02	0.07	0.02	0.10	0.03
capm60	0.08	-0.02	0.08	0.02	0.11	0.03
capm30	0.01	-0.05	0.03	0.01	0.05	0.01
capm90_2	0.07	0.07	0.07	0.04	0.10	0.07
capm60_2	0.06	0.05	0.06	0.05	0.09	0.07
capm30_2	-0.05	0.01	0.00	0.02	-0.01	0.02
capm90-ap	0.01	-0.05	0.05	0.00	0.07	0.00
capm60-ap	0.02	-0.06	0.04	-0.01	0.06	-0.02
capm30-ap	-0.05	-0.10	0.02	-0.03	0.02	-0.04
capm90-ap2	0.09	0.06	0.10	0.05	0.15	0.06
capm60-ap2	0.09	0.04	0.10	0.05	0.15	0.06
capm30-ap2	-0.01	-0.01	0.04	0.02	0.06	0.02

Unfortunately, in line with previous literature – Booth and Marcato [2004b] – we do not find any contemporaneous dependency (apart from Kendall’s Tau between IPD and capm90-ap2) to be significantly different from zero – we only report Spearman’s Rho values in table 4.9 (i.e. Pearson’s correlations and Kendall’s Tau coefficients yield similar results)³⁶. However, we find measures increasing to more than 0.10 when we adjust the Datastream index with our CAPM methodology – 0.15 and 0.11 Spearman Rho between IPD and respectively capm90-ap2 (or capm60-ap2) and capm60. Finally,

³⁶ This result is consistent with previous literature applying a WACC framework – e.g. Booth and Marcato [2004b].

main results show that this improvement in dependency does not hold if we unsmooth direct real estate returns.

Inter-temporal dependency measures with a valuation-based index show significant figures for all indexes at lags four to seven. With our CAPM methodology we also find significant dependencies at lags one to three (capm90, capm60, capm90-ap2 and capm60-ap2) which we do not find with a WACC methodology. Particularly, table 4.10 shows that the Spearman's Rho at one month lag is significant at a 5% level when we use either our illiquidity measure and a leverage figure computed with market values, or the Acharya-Pedersen's illiquidity measure and a leverage computed with book values. In the latter case, however we also find significant inter-temporal dependency with positive lags (i.e. private real estate markets leading real estate securities) and we then prefer the former because it suggests a clear lead/lag structure. Finally, both capm90 or capm60 show higher significant coefficients at each single lag (one to seven) than with original data.

Table 4.10: Inter-temporal Spearman's Rho coefficient between securitised returns and the IPD index (monthly)

				Marcato's illiquidity measure						Acharya-Pedersen's illiquidity measure					
				capm 90	capm 60	capm 30	capm 90_2	capm 60_2	capm 30_2	capm 90-ap	capm 60-ap	capm 30-ap	capm 90-ap2	capm 60-ap2	capm 30-ap2
ds rest	wacc	wacc2													
Lag +12	-0.04	-0.06	0.04	-0.03	-0.07	-0.08	0.08	0.01	-0.03	-0.06	-0.10	-0.15	0.03	0.01	-0.04
Lag +11	0.10	0.09	-0.01	0.14	0.09	0.07	0.15	0.07	0.04	0.11	0.07	0.00	0.12	0.09	0.05
Lag +5	-0.02	-0.03	0.01	0.02	0.01	-0.03	0.16*	0.12	0.02	0.00	-0.03	-0.08	0.21**	0.2**	0.11
Lag +4	-0.05	-0.06	-0.07	-0.01	-0.01	-0.05	0.16*	0.12	0.02	-0.01	-0.03	-0.07	0.21**	0.19**	0.10
Lag +3	-0.04	-0.05	-0.06	0.01	0.01	-0.02	0.15	0.12	0.03	-0.01	-0.03	-0.07	0.2**	0.19**	0.10
Lag +2	0.04	0.03	-0.11	0.10	0.11	0.06	0.10	0.08	-0.01	0.08	0.06	0.01	0.16*	0.15*	0.07
Lag +1	0.02	0.02	-0.14	0.10	0.11	0.05	0.07	0.06	-0.03	0.08	0.08	0.03	0.12	0.12	0.04
Lag 0	0.04	0.02	-0.14	0.10	0.11	0.05	0.10	0.09	-0.01	0.07	0.06	0.02	0.15	0.15	0.06
Lag -1	0.11	0.10	-0.09	0.18**	0.19**	0.14	0.15	0.14	0.05	0.18*	0.17*	0.14	0.21**	0.21**	0.14
Lag -2	0.12	0.11	-0.06	0.2**	0.21**	0.17*	0.22**	0.21**	0.13	0.2**	0.2**	0.18**	0.27***	0.29***	0.21**
Lag -3	0.15	0.13	-0.08	0.23**	0.23**	0.19**	0.19**	0.18**	0.09	0.23**	0.23**	0.21**	0.27***	0.27***	0.2**
Lag -4	0.27***	0.26***	-0.05	0.34***	0.35***	0.33***	0.25***	0.24***	0.15	0.31***	0.31***	0.31***	0.3**	0.3**	0.24***
Lag -5	0.21**	0.2**	0.00	0.27***	0.27***	0.24***	0.31***	0.3**	0.22**	0.23**	0.24**	0.23**	0.34***	0.33***	0.27***
Lag -6	0.18*	0.16*	-0.02	0.24**	0.24***	0.22**	0.23**	0.23**	0.13	0.23**	0.23**	0.24***	0.29***	0.28***	0.21**
Lag -7	0.24**	0.23**	0.04	0.3***	0.31***	0.29***	0.27***	0.29***	0.21**	0.27***	0.27***	0.29***	0.31***	0.32***	0.27***
Lag -8	0.07	0.06	-0.08	0.15	0.16*	0.14	0.14	0.16*	0.09	0.13	0.14	0.16*	0.19*	0.19**	0.16*
Lag -9	0.06	0.05	-0.08	0.14	0.16	0.15	0.05	0.08	0.02	0.11	0.13	0.16*	0.11	0.12	0.11
Lag -10	0.08	0.07	-0.04	0.12	0.13	0.13	0.09	0.11	0.09	0.05	0.06	0.09	0.10	0.12	0.11
Lag -11	0.04	0.03	0.03	0.07	0.10	0.12	0.14	0.17*	0.15	0.04	0.07	0.13	0.17*	0.19**	0.2**
Lag -12	-0.01	-0.03	0.00	-0.02	0.00	0.03	0.00	0.04	0.07	-0.07	-0.05	0.02	0.02	0.05	0.09

When we compare (either raw or adjusted) returns of real estate shares with an unsmoothed version of the IPD index, we only find coefficients for lag one and three being higher than the ones shown with valuation-based returns (see table 4.11). Moreover, we obtain a significant positive dependency at the positive eleventh lag, which suggests a non clear lead/lag structure between unsmoothed IPD returns and adjusted securitised returns. This finding is in line with the one of no improvement in contemporaneous dependencies obtained when unsmoothing direct real estate indexes. We believe this may be due to two different explanations and acknowledge a need for further investigation. Firstly, since we do not find vehicle-based performances leading unsmoothed valuation-based returns, this result may suggest that information are incorporated first in private real estate markets and subsequently in public ones. If we consider the unsmoothed version of the IPD index as a proxy for a transaction-based index, in fact, we could possibly argue information are firstly priced in the transaction market (i.e. where deals are completed). The valuation market then will adjust its estimate with a temporal lag and this is reflected in the dependency pattern with the IPD series. On the other hand however, the pricing of real estate shares may be based on the valuation of underlying assets (i.e. property portfolios) that is influenced by smoothing. As a consequence smoothing may be reflected in stock price movements, this leading to a better relationship between direct and indirect real estate returns when direct returns are not unsmoothed.

Table 4.11: Inter-temporal Spearman's Rho coefficient between securitised returns and the unsmoothed IPD index (monthly)

				Marcato's illiquidity measure						Acharya-Pedersen's illiquidity measure					
ds rest wacc wacc2				capm 90	capm 60	capm 30	capm 90_2	capm 60_2	capm 30_2	capm 90-ap	capm 60-ap	capm 30-ap	capm 90-ap2	capm 60-ap2	capm 30-ap2
Lag +12	-0.03	-0.04	0.03	-0.06	-0.06	-0.07	0.03	0.01	0.00	-0.10	-0.09	-0.09	0.00	0.00	-0.03
Lag +11	0.21**	0.22**	-0.08	0.22**	0.21**	0.19*	0.08	0.06	0.06	0.23**	0.22**	0.17*	0.08	0.08	0.07
Lag +5	0.01	0.01	0.07	0.01	0.01	0.00	0.00	0.01	0.00	0.03	0.03	0.01	0.06	0.08	0.09
Lag +4	-0.04	-0.04	-0.12	-0.02	-0.02	-0.03	0.03	0.03	0.00	0.01	0.03	0.04	0.04	0.04	0.01
Lag +3	0.04	0.03	-0.04	0.05	0.06	0.05	0.08	0.10	0.08	0.03	0.01	0.00	0.10	0.11	0.09
Lag +2	0.07	0.07	-0.07	0.09	0.10	0.09	-0.02	-0.03	-0.05	0.09	0.09	0.07	0.01	0.01	-0.01
Lag +1	-0.03	-0.03	-0.06	0.02	0.04	0.00	-0.07	-0.06	-0.08	0.03	0.05	0.05	-0.06	-0.05	-0.07
Lag 0	0.03	0.02	-0.05	0.03	0.03	0.01	0.07	0.07	0.02	0.00	-0.02	-0.04	0.06	0.06	0.02
Lag -1	0.18*	0.18**	0.05	0.2**	0.2**	0.19**	0.10	0.11	0.09	0.2**	0.21**	0.22**	0.14	0.15	0.15
Lag -2	0.05	0.05	0.00	0.09	0.11	0.09	0.15*	0.16*	0.13	0.11	0.12	0.12	0.16*	0.18*	0.14
Lag -3	0.12	0.11	-0.03	0.16*	0.14	0.13	0.07	0.08	0.03	0.14	0.12	0.12	0.12	0.10	0.07
Lag -4	0.24**	0.24**	0.09	0.22**	0.24**	0.25***	0.14	0.14	0.11	0.18*	0.19**	0.21**	0.11	0.12	0.11
Lag -5	-0.06	-0.06	0.00	-0.02	-0.04	-0.05	0.18*	0.18*	0.16*	-0.03	-0.03	-0.02	0.17*	0.16*	0.15
Lag -6	0.02	0.01	-0.03	0.02	0.04	0.05	-0.10	-0.07	-0.12	0.04	0.04	0.05	-0.03	-0.02	-0.04
Lag -7	0.18*	0.17*	0.10	0.18*	0.19**	0.19**	0.10	0.12	0.14	0.13	0.14	0.15	0.09	0.11	0.12
Lag -8	-0.19**	-0.19**	-0.24**	-0.13	-0.12	-0.13	-0.12	-0.12	-0.13	-0.10	-0.08	-0.07	-0.10	-0.10	-0.08
Lag -9	-0.03	-0.03	-0.05	0.00	0.00	0.00	-0.13	-0.10	-0.11	-0.01	-0.01	0.00	-0.07	-0.06	-0.05
Lag -10	0.10	0.09	0.11	0.05	0.06	0.07	0.12	0.13	0.15	-0.02	-0.02	0.01	0.07	0.09	0.10
Lag -11	-0.04	-0.04	0.09	-0.04	-0.01	0.03	0.10	0.12	0.13	0.01	0.04	0.09	0.13	0.13	0.17*
Lag -12	-0.05	-0.05	-0.05	-0.08	-0.09	-0.07	-0.2**	-0.16*	-0.13	-0.11	-0.11	-0.09	-0.17*	-0.14	-0.11

Table 4.12: Granger causality test (monthly)

				Marcato's illiquidity measure							Acharya-Pedersen's illiquidity measure						
				capm 90	capm 60	capm 30	capm 90_2	capm 60_2	capm 30_2	capm 90_2	capm 60-ap	capm 30-ap	capm 90-ap2	capm 60-ap2	capm 30-ap2	capm 90-ap2	capm 30-ap2
ipd				0.48	0.79	0.90	0.93	0.84	0.51	0.68	0.76	1.07	1.31	1.14	0.78		
unsm	0.38	0.34	0.51	0.48	0.69	0.67	1.00	0.87	0.53	0.56	0.56	0.52	1.44	1.24	0.84		
ds rest	2.46**	2.34**	0.99	1.20	1.10	1.39	0.42	0.47	0.13	0.23	0.39	0.77	0.42	0.44	0.18		
wacc	2.26**	2.15*	1.16	1.42	1.31	1.41	0.51	0.59	0.21	0.25	0.48	0.94	0.54	0.60	0.28		
wacc2	1.35	1.32	0.57	0.69	0.77	0.62	0.35	0.51	0.48	0.67	0.84	0.68	0.30	0.47	0.55		
capm 90	2.34**	2.3**	1.48	1.26	1.06	1.33	1.18	1.03	0.66	0.37	0.32	0.91	1.16	1.20	0.72		
capm 60	2.68**	2.6**	1.48	1.88*	1.81*	1.51	1.53	1.60	1.05	0.74	0.08	0.89	1.58	1.81*	1.20		
capm 30	3.41***	3.18***	1.14	1.18	1.05	0.83	1.43	1.53	1.06	0.60	0.49	0.04	1.55	1.78	1.23		
capm 90_2	3.11**	3.15***	1.22	1.18	1.05	0.83	1.15	1.15	1.21	1.08	0.92	0.59	0.26	0.64	0.87		
capm 60_2	2.97**	3.02**	1.20	1.52	1.31	1.09	0.72	1.68	1.74	1.17	1.02	0.72	0.21	0.12	0.67		
capm 30_2	2.72**	2.77**	0.91	1.27	1.06	0.82	0.99	1.68		0.87	0.74	0.40	0.61	0.68	0.05		
capm 90-ap	2.13*	2.07*	1.32	1.11	0.43	0.39	0.95	0.88	0.54		1.14	1.16	1.00	1.04	0.58		
capm 60-ap	2.13*	2.05*	1.36	1.29	0.51	0.54	1.29	1.47	0.91	1.00		1.33	1.39	1.64	1.01		
capm 30-ap	2.63**	2.44**	1.21	2.48**	2.23**	0.63	1.01	1.29	0.80	1.55	1.9*		1.21	1.55	1.01		
capm 90-ap2	3.61***	3.62***	1.51	1.35	1.11	0.83	0.26	0.41	0.90	1.21	1.02	0.63		1.03	1.21		
capm 60-ap2	3.05**	3.05**	1.41	1.68	1.41	1.06	0.19	0.30	1.14	1.34	1.19	0.82	0.64		1.54		
capm 30-ap2	2.6**	2.65**	1.13	1.65	1.34	0.90	0.32	0.40	0.26	1.19	1.02	0.55	1.04	1.44			

If we consider this matrix with only numbers (and excluding labels), we obtain a 17 by 17 matrix. Each cell in position (n,m) reports the F-statistic associated to the index in row n granger causing the index in column m. The opposite element (m,n) will contain the F-statistic associated to the index in row m granger causing the index in column n. As an example, 2.46 – cell (3,1) – represents the statistic of the test with null hypothesis “ftse does not granger cause ipd”. Likewise, 0.51 – cell (1,3) – represents the statistic of the test with null hypothesis “ipd does not granger cause ftse”. If both values are either significant or not significant, we cannot conclude that one variable granger causes the other one. This conclusion can only be reached if one of the two F-statistic is significant and the other one is not (as it happens in the example we chose).

Since dependency measures are significant up to the seventh lag, we finally test for Granger causality with seven lags, and expect to find significant results with securitised returns causing direct real estate ones. Table 4.12 reports F-statistics for all tests. If we exclude wacc2, all real estate shares indexes show a significant value in only one direction. We then conclude that securitised markets incorporate information quicker than unsecuritised valuation-based markets, the time lag being seven months.

4.7 CONCLUSIONS

Starting from recent findings about the use of net returns in a CAPM framework, we prove that when returns are net of illiquidity costs, the relationship between values of levered and unlevered companies (i.e. Rubenstein's formula) is no more valid if we introduce illiquidity costs for equity and they differ from zero. However this relationship holds if illiquidity costs in equity and debt markets are introduced and equal each other. When illiquidity costs of debt exceed the ones of equity, we theoretically demonstrate that the tax shield decreases.

We then propose a new measure of illiquidity costs that is used, along with the one proposed by Acharya and Pedersen [2005], in producing adjusted returns of real estate shares. We empirically find that returns of real estate shares are sensitive to illiquidity in both property and equity markets along with innovations in equity returns. We then

argue that, in line with previous finance literature, it is useful to consider this component when modelling real estate share prices.

In the second part of this chapter, we improve the real estate literature on price discovery by proposing a framework based on the capital asset pricing model net of illiquidity costs and adjusted for the leverage effect to obtain a proxy for direct real estate performances. We find that this measure mathematically implies and empirically shows a lower volatility than the original measure.

For an annual frequency, we find our model to yield an improvement in dependency with IPD from the original Datastream time series. This finding is not obtained by using a WACC model – e.g. Booth and Marcato [2004b] – and so we suggest our model should be preferred. Finally, in line with previous literature, we also conclude that unsmoothing improves the dependency between direct and indirect real estate returns.

However, when a monthly frequency is used, unsmoothing is not yielding any improvement and we justify this empirical result with two plausible explanations. Firstly, since we do not find vehicle-based performances leading unsmoothed valuation-based returns, this result may suggest that information are incorporated in private real estate markets first and subsequently in public ones. If we consider the unsmoothed version of the IPD index as a proxy for a transaction-based index, in fact, we could possibly argue that news are firstly priced in the market where properties are exchanged. This same information is then discovered in public markets and finally incorporated in valuations with a temporal lag of seven months. On the other hand however, real estate shares are probably priced through a valuation of underlying assets

(i.e. property portfolios) that is influenced by smoothing. Consequently stock price movements probably incorporate a smoothing effect, causing a higher dependency between securitised real estate returns and IPD than between securitised returns and unsmoothed ones. Finally, we empirically find that the securitised market incorporates information with a seven month lead over the unsecuritised market. This set of results has an implication for market efficiency which should lead to further investigation.

Since the CAPM methodology proved its efficiency³⁷ and efficacy³⁸ to create a proxy for direct real estate returns, we also argue this model may be used to construct historical indices, at least with an annual frequency, in markets where information about private real estate is not readily available. Main issues regarding the applicability of the CAPM model in markets with thin information will be discussed in the final chapter (see section 6.2.1).

Among several versions of the model, our analysis suggests a preference for a model using our measure of illiquidity costs, the leverage computed with market values and 60 rolling days to compute the beta coefficient. This index, in fact, shows the highest coefficients for both contemporaneous and inter-temporal dependencies.

³⁷ Little information is used.

³⁸ The similarity of risk/return profiles and the dependency between market returns and CAPM-adjusted returns improved.

Appendix

Proof of proposition 1

We start from the following balance sheet identity (EBIT indicates Earnings Before Interest and Tax):

$$r_i = \frac{(EBIT - r_d D)(1-t)}{S} \quad (A1)$$

If only equity markets show illiquidity costs, from 3 and A1 we find:

$$EBIT(1-t) = r_d D(1-t) + (R_f + c_i)S + \lambda(1-t) * \left[Cov\left(EBIT - c_i \frac{S}{1-t}, r_M - c_M\right) - DCov(r_d, r_M - c_M) \right] \quad (A2)$$

For an unlevered company (i.e. by assuming no debt, or $D=0$), A2 becomes:

$$EBIT(1-t) = (R_f + c_i)S^* + \lambda(1-t)Cov\left(EBIT - c_i \frac{S}{1-t}, r_M - c_M\right) \quad (A3)$$

We also know that, by assumption, equation 5 holds. Thus, if we equate the right hand sides of A2 and A3, we obtain:

$$(R_f + c_i)S^* = R_f D(1-t) + (R_f + c_i)S$$

which yields the proposition.

Proof of proposition 2

By following the previous steps (A2 and A3), from equations 3, A1 and 6, $EBIT(1-t)$ can be represented for respectively a levered and unlevered company as follows:

$$r_d D(1-t) + (R_f + c_i)S + \lambda(1-t) * \left[Cov\left(EBIT - c_i \frac{S}{1-t}, r_M - c_M\right) - D Cov(r_d - c_d, r_M - c_M) \right]$$

$$(R_f + c_i)S^* + \lambda(1-t) Cov\left(EBIT - c_i \frac{S}{1-t}, r_M - c_M\right)$$

If we equate the two previous formulas, we obtain:

$$(R_f + c_i)S^* = (R_f + c_d)D(1-t) + (R_f + c_i)S$$

and therefore:

$$V^* = S + D(1-t) \frac{(R_f + c_d)}{(R_f + c_i)} \quad (A4)$$

which yields the proposition

Proof of proposition 3

The Rubenstein's formula for β levered holds because $V^* = S + D(1-t)$. So, if we call this model number 1 and the one assuming illiquidity costs (i.e. equation A4) number 2, and take the differential of V^* on t , we obtain:

$$\frac{\partial V^{*1}}{\partial t} = -D$$

and

$$\frac{\partial V^{*2}}{\partial t} = -\frac{D(R_f + c_d)}{(R_f + c_i)}$$

Under the initial condition given in the proposition and being all values greater than 0, the second differential is smaller than the first one.

Proof of proposition 4

If $L' = \frac{S}{S + D(1-t)}$, then $L = (1 - L')$ represents our leverage ratio. Therefore, after few adjustments, we can re-express equation 10 for respectively levered and unlevered companies as follows:

$$E(r_i)^* = E(r_i + c_i) - L[E(r_i - c_i) - R_f]$$

which, given the initial conditions, yields the proposition.

Chapter 5

REPEATED-MEASURES REGRESSION MODELS AND THE CONSTRUCTION OF DIRECT REAL ESTATE INDICES

5.1 INTRODUCTION

So far we have used securitised property returns and information about the capital structure and liquidity of property companies to generate two proxies for direct (i.e. private) real estate returns. The use of individual property data – following an approach similar to the one adopted for current standard property indices – may represent an alternative method to create historical real estate indices in markets with thin information.

Returns computed from valuation-based indices are normally drawn from a population of standing investment properties only. This means that returns of both purchased properties and buildings developed during the year are not reflected in common measures of performance. Moreover, index construction methodologies similar to the ones used by Investment Property Databank (i.e. IPD) and the National Council of Real Estate Investment Fiduciaries (i.e. NCREIF) require the availability of periodic information about capital values of individual properties. The difficulty of gathering this type of information in less developed markets becomes even more critical when we are trying to construct long time series since we need a sequence of historical values to be found in companies' records. Consequently in markets with thin information this type of data is not available and its use should then be avoided when historical indices are to be constructed. In such circumstances it is clearly preferable to use few data-points containing significant information, which are easily accessible.

Moreover, if we assume market efficiency, all information should be reflected in transaction prices and price estimates (i.e. valuations). If this assumption is verified, capital values should also represent true estimates of transaction prices (i.e. there should be valuation accuracy). These two types of information can thus be used interchangeably and initial acquisition prices can be compared with most recent valuations to obtain an estimate of capital growth rates throughout the sample period. However, the use of only two observations for each property throughout the entire period³⁹ would only allow us to identify multi-period returns. In order to pass from multi-period returns of individual properties to periodic index performances, it is thus necessary to calculate a periodic average figure for each individual property and then to compute a cross-sectional average of individual property returns for each period. Repeated-sales regression techniques have been developed in the literature to estimate index returns following exactly this process.

An example may clarify this point. Let us assume that a property is bought in 1985 for £1,000 and it shows a capital value of £1,900 at the end of 2002 (for simplicity we assume no capital expenditures throughout the 17-year period). The increase in value equals £900 and it corresponds to a capital growth of 90% over the 17-year period. If we want an estimate of the average annual return (i.e. AAR), we then need to annualise this figure as follows: $AAR = (1 + 90\%)^{1/17} - 1 = 3.85\%$. Once periodic returns for each

³⁹ The first observation (i.e. initial acquisition price) refers to the beginning of the holding period and the second one (i.e. most recent valuation) to the end of the holding period.

individual property are computed, they are aggregated at the index level for each year with either a geometric or an arithmetic mean and assuming either equally-weighting or capital-weighting.

In this chapter we apply four different types of repeat-measures regression (RMR) techniques to obtain capital growth rates from individual property data. These types of indices need a smaller amount of information than standard valuation-based ones since no periodic appraisals are needed to infer periodic returns. More precisely the construction of a capital growth index using RMR techniques requires three basic pieces of information:

- purchase prices, along with the dates of the acquisition;
- intermediate cash flows such as capital expenditures⁴⁰ and capital receipts⁴¹. These are normally available in company records. Even if it is possible to apply some index construction methods which do not require this type of information, its inclusion is meant to avoid a possible distortion in return estimates because of their impact on capital appreciation rates;
- most recent valuations (in our study all figures refer to the last measurement period of the sample), depending upon their availability.

⁴⁰ Expenses relating to the refurbishment or development of a property, which have a direct impact on the value of the property itself.

⁴¹ Receipts for changes in the owner's interest in the property (e.g. sale of a portion of the building).

The type of information needed to create RMR indices makes our problem similar to the estimation of periodic returns from transaction-based indices rather than valuation-based ones (see section 2.3 for a detailed discussion of differences between the two methods). More specifically, by using initial purchase prices and most recent valuations, our estimation problem can be solved with repeated-sales regression (i.e. RSR) techniques, where the most recent valuation is used as a proxy for sale prices.

In its original (i.e. not hybrid) form, a RSR index does not require any estimation of implicit prices of qualitative characteristics (e.g. lifts, dwelling age, etc.) and then avoids complications associated with data availability, variable selection (i.e. omitted variables issue) and specification of the correct functional form (i.e. linearity vs. non-linearity).

However, this method conveys some shortcomings, the most significant of which is a sample selection bias. Most databanks of real estate prices include a very low percentage of properties transacted at least twice along the measurement period, and this issue is even more problematic when the analysis refers to a short time horizon (i.e. nowadays in the UK IPD databank each property is transacted every ten years on average, but in markets with thin information this period may be much longer). This means that the sample may represent a very small proportion of up-to-date transaction prices, and most of all only a specific segment of the market (i.e. more frequently transacted properties would probably be prime properties).

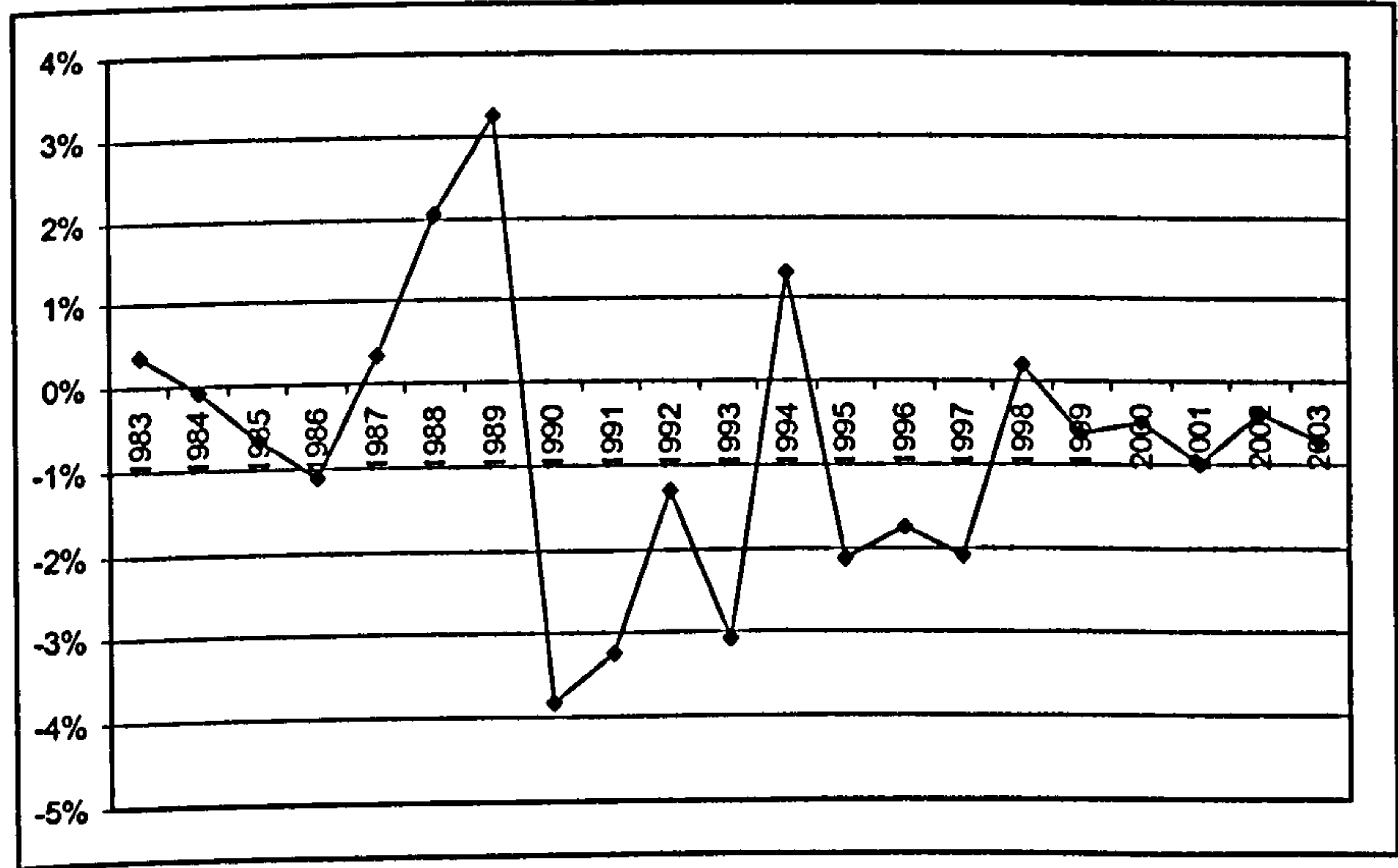
This bias can be compared with the survivorship bias studied in other areas of the finance literature, but there exists a difference between RMR techniques and “pure RSR methods”. In fact, since we compare – for each property – the initial purchase price with the most recent valuation using a sample period between 1980 and 2002, we only consider assets that have been purchased after 1980 and are still held as standing investments at the end of the period. This means we exclude buildings that have been sold during the overall period. As a result, we would expect to find our results to represent a valuation rather than transaction-based index (i.e. it is as if we assume the acquisition price is equal to the first valuation and we estimate our returns without considering intermediate valuations).

A second issue which arises from the employment of prices and valuations interchangeably is the comparability between these two measures. A recent study accomplished by IPD on behalf of the Royal Institute of Chartered Surveyors [2005] shows that on a sample of 1,216 sales recorded by IPD in 2003, the average difference between capital value and sale price at the time of sale is 9.9% in absolute terms, with 78% of valuations within a boundary of +/- 15% from sale prices. In a portfolio context, however, this result is destined to be improved since positive and negative errors cancel each other out. A recent study by Marcato and Manstretta [2005] showed that, on average, the valuation error is equal to 5.3% (median 3.6%) and -0.7% (0.2%) for respectively sales and purchases. The smaller error found for purchases than for sales is due to the fact that when a valuer appraises a property, he/she knows the previous

acquisition price – which may represent an anchor for the following valuation – but he/she does not know the following sale price.

As far as purchase prices are concerned, valuation accuracy seems to be guaranteed, with the exception of very unstable markets (e.g. see late 1980s and early 1990s in graph 5.1). The only significant consequence on performance measurement is in 1990, when the valuation error (measured as the difference between adjusted purchase price and subsequent valuation over the adjusted price) is negative and equal to -4% , compared with a positive error ($+3.3\%$) in 1989. Last computed figures also signal a clear improvement throughout time. Specifically, they show that there has been a smaller and constant ‘valuation error’ (less than 1% in absolute value) since 1999.

Graph 5.1: UK valuation error of purchases (excluding outliers)



This chapter is structured as follows: section 5.2 describes four different methodologies we adopt to create historical indices starting from information about purchase price, intermediate cash flows and last available valuation (in this analysis referring to 31 December 2002 for all properties). In the UK (and even more in markets with thin information) it is not possible to apply the same methodology to construct a monthly RMR index because the sample would not be big enough. We then decide to restrict our analysis to an annual frequency.

Section 5.3 contains a description of individual property data used in this study. The sensitivity of regression methods to the quality of inputs required a careful data cleaning process, which is also explained in detail.

Section 5.4 contains main results and a discussion of the differences in descriptive statistics and time series properties shown by the four indices, in comparison with both original and unsmoothed valuation-based returns. If valuations truly reflect prices, the two types of indices (RMR and current IPD index) are expected to show similar descriptive statistics, a high degree of dependency and the same cyclical pattern. If the sample is representative of the overall IPD universe and these hypotheses are not verified, there are two plausible explanations that may occur either independently or jointly. On one hand interim annual valuations (between purchase and last appraisal dates) used by current indices may contain more information (signalling the existence of a non efficient market). In fact, as we assume that values reflect prices (perfect valuation accuracy), then prices should include all available information. On the other

hand, we could infer that valuations do not exactly reflect prices either because of valuation inaccuracy (instantaneous error), or because of lagging issues such as a longer period needed to incorporate new information in valuations (inter-temporal error), or appraisals made at different points in time (aggregation issue).

Finally, in section 5.5 we draw main conclusions.

5.2 METHODOLOGY

From the specifications that have been suggested in the literature, we apply two different models and suggest other two methodologies to obtain a total of four indices:

- A simple model using geometric averages is used to compute capital growth rates without using intermediate cash flows. This methodology was previously applied to several datasets (mainly housing prices) and allows us to use a small set of information (i.e. two observations per property: initial purchase price and most recent valuation). This model would be particularly useful if intermediate capital expenditures/receipts cannot be obtained from primary sources;
- A more elaborate model using capital-weighted arithmetic averages makes index results more directly comparable to standard valuation-based returns. This methodology – already applied for both commercial and residential indices in the

US – requires intermediate cash flows. The availability of such information limits its application in markets with thin information. However, this type of data should be easily available from primary sources.

- Finally, two models compute either capital-weighted or equally-weighted arithmetic averages and use standard methods of valuation-based indices. However, they are applied backwards rather than forwards in time. This methodology uses information (i.e. initial purchase prices) that is normally disregarded in the construction of current market indices and may be useful to understand the impact of such data on index figures.

5.2.1 BMN model

The first method we apply is a repeated-sales regression suggested by Bailey, Muth and Nourse in 1963 (i.e. BMN method). Interim cash flows and their impact on index returns (i.e. CFs between acquisition and valuation dates) are not considered. In fact this model was initially developed for residential properties that are less subject to refurbishment activities than commercial buildings.

As a starting point, we show a brief example to explain how this model works in principle. Let us assume not-directly-observable true capital growth rates (i.e. TCGRs) equal to 6%, 4% and 5% respectively in year 1, 2 and 3. The only transactions and

valuations during the period are reported in table 5.1.

Table 5.1: Transaction and valuation data

year 1	Purchase price year 2	year 3	End year 3 valuations
	-1000.00		1092.00
		-1000.00	1050.00
-1000.00			1157.52

With TCGRs, we mean that if we use them to compound the purchase price for each property, we exactly obtain its last valuation. If we apply this process to our dataset we find that:

$$\left\{ \begin{array}{l} P1: 1,000.00 * (1+4\%) * (1+5\%) = 1,092.00 \\ P2: 1,000.00 * (1+5\%) = 1,050.00 \\ P3: 1,000.00 * (1+6\%) * (1+4\%) * (1+5\%) = 1,157.52 \end{array} \right.$$

When the true growth rates of 6%, 4% and 5% are applied to each one of the three properties, the valuation at the end of the third year perfectly reflects and implies those rates as the best estimation of capital returns for this population. However, in the real world, we do not know TCGRs a-priori, but we want to estimate them from information

on purchase prices and valuations. In order to do so, we have to solve the following system of equations:

$$(1) \quad \begin{cases} EQ1: 1,000.00 * (1+r_2) * (1+r_3) = 1,092.00 \\ EQ2: 1,000.00 * (1+r_3) = 1,050.00 \\ EQ3: 1,000.00 * (1+r_1) * (1+r_2) * (1+r_3) = 1,157.52 \end{cases}$$

In this very simple example, where a precise single solution is implied by the very fact that valuations have been simply computed from pre-defined capital appreciation rates, we could solve EQ2 first. We could then use the solution for r_3 in EQ1 in order to obtain r_2 . We finally compute r_1 from EQ3⁴².

However, because capital growth rates have to be estimated by minimising the approximation error, we rearrange (1) into:

$$\begin{cases} EQ1: \frac{1,092.00}{1,000.00} = (1+r_2) * (1+r_3) \\ EQ2: \frac{1,050.00}{1,000.00} = (1+r_3) \\ EQ3: \frac{1,157.52}{1,000.00} = (1+r_1) * (1+r_2) * (1+r_3) \end{cases}$$

⁴² The estimation of real estate returns can be compared to the computation of spot yield curves from bond prices.

At this point, we linearise the system by taking the logarithms of both sides of the three equations:

$$\left\{ \begin{array}{l} EQ1: \quad \text{Ln}\left(\frac{1,092.00}{1,000.00}\right) = \text{Ln}[(1+r_2) * (1+r_3)] \\ \\ EQ2: \quad \text{Ln}\left(\frac{1,050.00}{1,000.00}\right) = \text{Ln}[(1+r_3)] \\ \\ EQ3: \quad \text{Ln}\left(\frac{1,157.52}{1,000.00}\right) = \text{Ln}[(1+r_1) * (1+r_2) * (1+r_3)] \end{array} \right.$$

and we then transform it into an additive system [i.e. $\text{Ln}(a*b) = \text{Ln}(a) + \text{Ln}(b)$]:

$$(2) \quad \left\{ \begin{array}{l} EQ1: \quad \text{Ln}\left(\frac{1,092.00}{1,000.00}\right) = \text{Ln}(1+r_2) + \text{Ln}(1+r_3) \\ \\ EQ2: \quad \text{Ln}\left(\frac{1,050.00}{1,000.00}\right) = \text{Ln}(1+r_3) \\ \\ EQ3: \quad \text{Ln}\left(\frac{1,157.52}{1,000.00}\right) = \text{Ln}(1+r_1) + \text{Ln}(1+r_2) + \text{Ln}(1+r_3) \end{array} \right.$$

We finally rewrite system (2) including all three compounding factors in each equation with weight 0 in periods when the property was not held:

$$\left\{ \begin{array}{l} EQ1: \quad \text{Ln}\left(\frac{1,092.00}{1,000.00}\right) = \text{Ln}(1+r_1)*0 + \text{Ln}(1+r_2)*1 + \text{Ln}(1+r_3)*1 \\ \\ EQ2: \quad \text{Ln}\left(\frac{1,050.00}{1,000.00}\right) = \text{Ln}(1+r_1)*0 + \text{Ln}(1+r_2)*0 + \text{Ln}(1+r_3)*1 \\ \\ EQ3: \quad \text{Ln}\left(\frac{1,157.52}{1,000.00}\right) = \text{Ln}(1+r_1)*1 + \text{Ln}(1+r_2)*1 + \text{Ln}(1+r_3)*1 \end{array} \right.$$

This is nothing else than using dummy variables to apply linear regression procedures in order to estimate rates of return. A matrix of 1 - 0 variables indicating the holding period for each property is then constructed. The single element of the matrix (i.e. x_{mn}) is equal to either 1 or 0 depending upon the fact that property m is respectively included in or excluded from the portfolio during year n :

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

For example the first horizontal vector of the matrix $[x_{11} \ x_{12} \ x_{13}]$ indicates that property 1 has been purchased at the beginning of year 2 and held for two periods.

The system of equations can finally be expressed as a simple linear function that is used to estimate the parameters:

$$Y = X\beta + \varepsilon$$

where Y represents the $m \times 1$ vector of log measure relatives for each observation, β is the estimated $n \times 1$ vector of period-by-period log compounding factors [i.e. $\text{Ln}(1+r_t)$],

$$X = \begin{bmatrix} x_{11} & x_{11} & \dots & x_{1n} \\ x_{21} & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ x_{m1} & \dots & \dots & x_{mn} \end{bmatrix} \text{ represents the } m \times n \text{ matrix of holding period dummy variables}$$

with m and n respectively equal to the number of properties and years, and ε is the $m \times 1$ vector of error terms.

In this simple example with 3-by-3 dimensions (observations-by-years), we easily find a unique solution. However, in the real world we would find many more degrees of freedom (i.e. the number of properties would be much higher than the number of intervals). Consequently, if the equations are not consistent, a single precise solution might not exist. We have then to estimate a solution which minimises the sum of squared residuals: $\varepsilon_1^2 + \varepsilon_2^2 + \dots + \varepsilon_n^2$. This represents an ordinary least squares estimation (i.e. OLS) that in our case will give the following solutions:

$$\hat{\beta}_1 = 5.83\% = \text{Ln}(1 + 6\%)$$

$$\hat{\beta}_2 = 3.92\% = \text{Ln}(1 + 4\%)$$

$$\hat{\beta}_3 = 4.88\% = \text{Ln}(1 + 5\%)$$

By then converting this solution, we can compare the results with (1):

$$\hat{r}_1 = \exp(\hat{\beta}_1) - 1.$$

5.2.2 GG Model

Since we use commercial property data, capital expenditures may become a significant driving factor of capital appreciation rates. Asset managers normally use them to enhance performances and we then need to include these intermediate cash flows in our methodology. Since the BMN estimation procedure (with log relative measures used as independent variables) does not allow us to consider them, we also apply the Geltner and Goetzmann [2000] model (i.e. the so called GG method) that incorporates capital expenditures/receipts happening between the dates of acquisition and most recent valuation for each property.

The basic model is derived from a Net Present Value (i.e. NPV) formula applied to each property:

$$0 = -P_t + \left(\frac{1}{1+r_{t+1}}\right)CF_{t+1} + \left(\frac{1}{1+r_{t+1}}\right)\left(\frac{1}{1+r_{t+2}}\right)CF_{t+2} + \dots + \left(\frac{1}{1+r_{t+1}}\right)\dots\left(\frac{1}{1+r_{t+n}}\right)(CF_{t+n} + V_{t+n})$$

where P_t is the purchase price at time t , V_{t+n} represents the valuation at time $t+n$, CF_t is the cash flow at time t ⁴³, and r_t indicates the performance measure at time t .

⁴³ Geltner and Goetzmann use either the sum of net income and capital expenditures/receipts or only capital expenditures/receipts to compute respectively total returns and capital growth rates. Since we only have information about capital expenditures/receipts (and not about income) we restrict our analysis to capital appreciation rates.

The estimation equation is then expressed as before, but with a different vectors/matrix composition:

$$Y = X\beta + \varepsilon$$

where Y represents an $m \times 1$ vector, with y_i equal to either the purchase price if property i has been bought at the index base date or zero otherwise; X is a $m \times n$ matrix containing the cash flows generated by each property in each period (i.e. purchase prices and capital expenditures are negative; last valuations and capital receipts are positive); β is the $n \times 1$ vector of estimated discounting factors; and ε represents the $m \times 1$ vector of error terms.

If we refer back to our simple example and suppose only one interim cash flow of £100.00 for the last property during year 2 and a changed final value (now equal to £1,257.52), we would obtain the following estimation equation:

$$\begin{bmatrix} 0 \\ 0 \\ 1,000 \end{bmatrix} = \begin{bmatrix} -1,000.00 & 0 & 1,092.00 \\ 0 & -1,000.00 & 1,050.00 \\ 0 & -100.00 & 1,257.52 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix}$$

Finally, returns are computed from estimated betas as follows:

$$\hat{r}_i = \frac{\hat{\beta}_{i-1}}{\hat{\beta}_i} - 1$$

This model, however, shows a bias due to the inclusion of appraised values in the X matrix on the right-hand side of the equation. Estimated market values, in fact, contain random appraisal error and idiosyncratic return noise and this may cause OLS estimation to be biased. As Shiller [1991] suggests, a solution to this problem is found by applying a generalised least squares estimation procedure (i.e. GLS), which uses the time interval between the date of the acquisition and the date of its last valuation in order to adjust for heteroskedasticity in the error terms. Each observation is thus weighted by the inverse of the its holding period. Properties with a longer period will be weighted less than properties with a shorter period (i.e. the underlying assumption is that new information shows a greater certainty and should then be weighted more than old information).

This type of procedure is also applied in our model. The three steps involved in a GLS procedure are as follows:

- 1) OLS estimation of the basic model;
- 2) Regression of the squared error terms obtained in the first step OLS estimation on a constant and the time between the two transactions;
- 3) GLS estimation of the first equation after having divided each observation by the square root of the fitted value obtained in step two.

5.2.3 BW model

The last method uses data from each period independently. We start to compute 2002 returns by using only information on properties bought in 2002. Then we work out the 2001 return for properties bought in 2001 by assuming that their 2002 capital growth rates matched the index capital appreciation rates found in 2002. We then continue this process going backwards until 1981.

In this section we present our methodology in detail. We start computing an index return in 2002 by using information referring to properties bought during 2002. We apply the following formula to each property i to obtain its annual return:

$$Ret_{i,2002} = \frac{CV_{i,2002} - P_{i,2002} - C_{i,2002}}{P_{i,2002} + C_{i,2002}}$$

where $CV_{i,2002}$ stands for capital value of property i at the end of 2002, $P_{i,2002}$ is the purchase price of property i in 2002 and $C_{i,2002}$ represents capital expenditures/receipts of property i in 2002. As we do not have any information about the month in which capital expenditures occurred, we assume they refer to the beginning of the year (i.e. same date of acquisition for the first year of the holding period).

We obtain the 2002 index return, by simply computing an average of n individual property returns. Firstly, we compute an equally weighted arithmetic index (i.e. no capital weighting is applied) as follows:

$$Index\ Ret_{i,2002} = \frac{\sum_{i=1}^n Ret_{i,2002}}{n} \quad (3)$$

We then apply the same methodology to compute the 2001 return. The formula for each property return is obtained as follows:

$$Ret_{i,2001} = \frac{CV_{i,2001} - P_{i,2001} - C_{i,2001}}{P_{i,2001} + C_{i,2001}}$$

where, since we only have capital values in 2002, $CV_{i,2001}$ is obtained by:

- discounting the 2002 capital value back for 1 year with a discount rate equal to the 2002 index return and
- subtracting/adding 2002 capital expenditures/receipts:

$$CV_{i,2001} = \frac{CV_{i,2002}}{(1 + Index\ Ret_{i,2002})} - C_{i,2002} \quad (4)$$

Following the same methodology, we can compute each capital value in 2000 as follows:

$$CV_{i,2000} = \frac{CV_{i,2001}}{(1 + Index Ret_{i,2001})} - C_{i,2001} \quad (5)$$

By substituting (4) in (5), we can then obtain the final formula for capital values in 2000:

$$CV_{i,2000} = \frac{\frac{CV_{i,2002}}{(1 + Index Ret_{i,2002})} - C_{i,2002}}{(1 + Index Ret_{i,2001})} - C_{i,2001}$$

Finally, we apply this procedure to each year going back to 1981 and generate a capital growth series, which we call BW_EW series (from backward method, with an equally weighting procedure).

Furthermore, we also create a fourth index by using a capital-weighted backward looking method (i.e. BW_CW). We obtain this new series by substituting the following equation to equation (3):

$$Index Ret_{i,t} = \frac{\sum_{i=1}^n Ret_{i,t} * CV_{i,t-1}}{\sum_{i=1}^n CV_{i,t-1}}$$

We acknowledge that this method leads to a loss of information because returns are computed for each period using exclusively properties bought during that period (i.e. 2000 returns are computed using properties bought in 2000)⁴⁴. Consequently, properties acquired between the start of the sample period and year t will not be considered even if they would have been included in the index computed with a standard valuation-based methodology. An example may be useful to support our argument. Let us focus on the estimation of the index return in 2001, which represents an extreme case of information loss. To calculate the index return in 2001, the BW methodology only uses properties bought in 2001. Since these properties do not show capital values at the end of 2001 (necessary to compute 2001 returns) are not available, we obtain them by discounting 2002 end-year capital values at a discounting rate being equal to the 2002 index return for all properties (i.e. the underlying assumption is that all properties bought in 2001 showed a 2002 capital growth equal to the capital growth of the market). Consequently, even if there are properties acquired before 2001 and showing a 2002 year-end valuation, we do not use these data to compute the 2001 index return⁴⁵.

Notwithstanding this problem, the BW method allows us to compute a return which is independent of previous returns. Since the size of our sample tends to become smaller the further we go back into the past, we prefer long-term returns not influencing the

⁴⁴ This method contrasts with the one used by current standard valuation-based indices, which only use standing investments to compute market returns (i.e. they exclude properties transacted and developed during the period).

⁴⁵ Contrarily to the BW methodology, current standard valuation-based indices would use this information through periodic valuations.

estimation of most recent ones. In fact we expect to find the latter to reflect “true performances” (as from IPD) better than the former. Consequently, if on one hand we “bear” an information loss, on the other hand we obtain benefits when we use a thin sample, mostly during the first years of our measurement. The impact of a small sample is even more significant in markets with little information, and particularly in the computation of historical series. For this reasons we think the BW methodology can represent a suitable model to generate an historical index of private real estate returns in markets with thin information.

5.2.4 Index comparison

We compare both the original and the unsmoothed valuation-based index with the Datastream Real Estate Sector index and several CAPM-adjusted Datastream indices, following the main steps described in 3.2.3 to analyse:

- cyclical patterns (i.e. peaks, uprising and down-falling phases);
- descriptive statistics⁴⁶ and deviations from normality⁴⁷;

⁴⁶ E.g. mean, median, standard deviation, kurtosis, skewness and autocorrelation function.

⁴⁷ Additionally to the Jarque-Bera test, we compute the *Lilliefors statistic* – a modified version of the Kolmorov-Smirnov goodness-of-fit statistic. It is very intuitive and it tests for normality when the population parameters are unknown. After ranking data values from the smallest to the largest one (x_1, x_2, \dots, x_n), the average (μ) and variance (σ^2) of the unbiased sample estimators are used to standardize data values. If $\Phi(z)$ denotes the standard normal cumulative distribution function and the empirical distribution function (i.e. EDF) of the data for every z is computed as $F_n(z) = \frac{\text{number of } z_{(k)}\text{'s} \leq z}{n}$, the

- contemporaneous and inter-temporal dependency between (both original and adjusted) securitised and unsecuritised real estate returns⁴⁸;
- causality effects between direct and indirect property performances⁴⁹.

5.3 DATA DESCRIPTION

Investment Property Databank directly provided acquisition price and date, annual capital expenditures and 2002 capital values for more than 7,000 randomly chosen properties that have been bought from 1980 onwards and are still part of the IPD databank at the end of 2002.

We cleaned the data by excluding properties if:

- they have been completely redeveloped during the measurement period (i.e. we want to measure the same type of performance the IPD index shows);
- their sector changed over the analysis period (e.g. the pricing for office and retail properties may differ);

Lilliefors test statistics – with a p-value computed from the Dallal-Wilkinson (1986) formula – represents the maximum vertical distance between $F_n(z)$ and $\Phi(z)$: $L = \max\{F_n(z) - \Phi(z), -\infty \leq z \leq \infty\}$.

⁴⁸ Pearson's correlation coefficient, Kendall's Tau and Spearman's Rho.

⁴⁹ Granger causality test.

- their average annual return over the holding period was higher than +50%, or lower than -50%.

Table 5.2: Sample composition

Year	No. of properties	Cumulative No. of properties	Database value (£ billions)	Cumulative Database value (£ billions)
1981	47	47	0.18	0.18
1982	39	86	0.15	0.33
1983	45	131	0.14	0.47
1984	41	172	0.42	0.90
1985	47	219	0.47	1.37
1986	43	262	0.27	1.64
1987	103	365	0.56	2.20
1988	155	520	0.72	2.93
1989	143	663	0.85	3.78
1990	88	751	0.83	4.60
1991	122	873	0.70	5.30
1992	150	1023	0.91	6.21
1993	206	1229	1.65	7.86
1994	394	1623	4.12	11.98
1995	232	1855	1.60	13.58
1996	379	2234	2.17	15.74
1997	583	2817	4.67	20.41
1998	588	3405	5.11	25.51
1999	655	4060	5.92	31.44
2000	825	4885	8.08	39.52
2001	640	5525	6.38	45.89
2002	944	6469	8.94	54.83
Total	6469		54.83	

Table 5.2 shows our sample composition year by year. First of all, we think our sample size is quite significant: £ 54.8 billion and 6,469 properties are included in the index from 1981 to 2002. However, we also notice that the sample size tends to diminish if we move backwards from 2002 to 1981. Particularly, during the first six years the annual sample is very thin and only less than fifty properties are available (i.e. this is a sample of properties bought during the n^{th} year, not showing complete redevelopment throughout the period and still included in the database at December 2002). Since the sample is so small, we believe that regression techniques using the whole time period may be biased if the first six years are included in our analysis.

The empirical analysis will also show the impact of such thin sample and we will then base our final results on a reduced historical period starting in 1987, when we have 103 properties worth £ 600 million. The sample continuously increases throughout time and exceeds the 1 billion threshold starting from 1993, with 206 properties. Finally, the sector composition reflects weights of retail, offices and industrial properties, which are similar to the ones included in the IPD Annual index.

Finally, in order to work on an annual basis we assume that all properties have been purchased at the beginning of the year. This is a plausible assumption if we consider the interval needed to complete a transaction in any real estate market. As reported in Bond et al. [2004], the price of a property is normally fixed six months before its transaction

comes to completion⁵⁰. We then assume that on average each transaction has been completed in June – some would show a completion date in January, some others in December – and transaction prices then refer to the beginning of the year.

5.4 RESULTS

If we plot the original IPD return series and the four RMR ones (see graph 5.2), we observe three main patterns:

- during the first period (i.e. 1981 – 1988) RMR returns behave differently from IPD ones, which are constant and stable throughout the first seven years;
- the GG method determines a significant spike in 1984-1985, which cannot be explained with any major event in real estate markets and which we attribute to a problem of sample size collapsing in those years. However, a similar but less pronounced behaviour is shown by all other RMR indices. This finding may suggest two possible explanations: either standard valuation-based methodologies are not able to record a rise and subsequent fall in returns over that period – IPD returns in fact remain flat in those years –, or the availability of very little information during

⁵⁰ “The median time to sale, at 190 days, is a more representative figure. That still represents six months to sell the typical property from the funds examined. The longest stage is the period from initiation to heads of terms (median 88 days)”. Source: IPF Liquidity Study [2004].

earlier years affects the return estimation significantly. The latter explanation tends to be preferred if this finding is related to the previous one;

- during the last ten years, all performance measures tend to converge. Two main factors may explain this trend: on one hand, the most recent dataset is more reliable and fully-informed than the one in earlier years; on the other hand, performance measurement is easier in stable markets (i.e. late 1990s, beginning of 2000s) than in unstable markets (i.e. late 1980s, beginning of 1990s).

Graph 5.2: RMR series plotted against the IPD index (sample: 1980-2002)

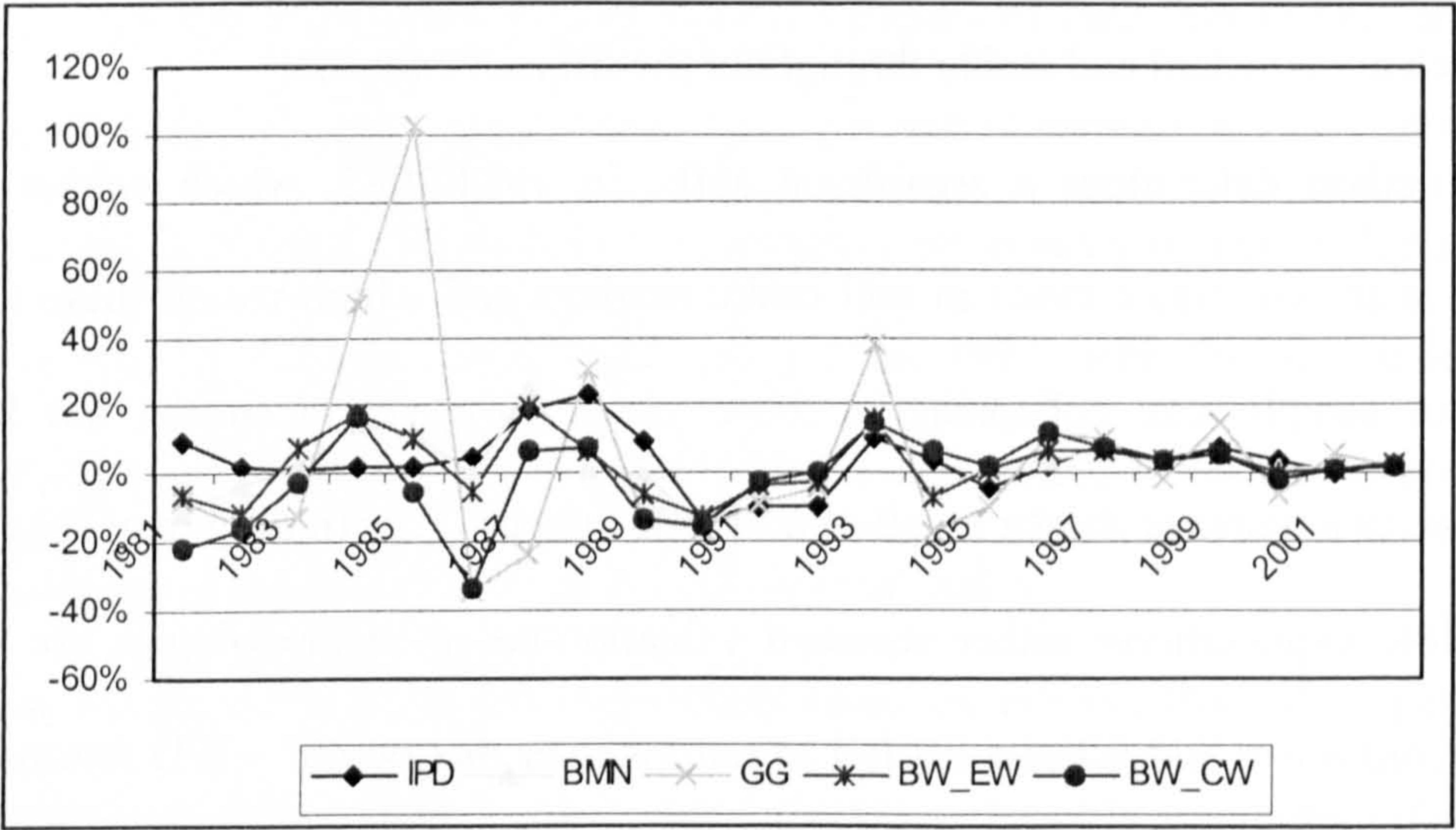


Table 5.3: Descriptive statistics (sample: 1980-2002)

	IPD	UNSM	BMN	GG	BW_EW	BW_CW
Average Return	3.3%	3.0%	3.0%	4.9%	2.9%	0.0%
Standard Deviation	10.0%	16.0%	9.9%	36.0%	10.6%	13.8%
Return per unit of risk	32.8%	19.0%	29.8%	13.6%	27.0%	-0.1%
Skewness	0.17	-0.10	0.42	1.87	0.19	-1.19
Kurtosis	0.57	1.54	2.84	0.17	0.65	0.72
Median	2.6%	1.3%	2.2%	-4.4%	2.7%	2.2%
Autocorrelation	0.44	0.23	0.07	0.00	0.10	0.23

Table 5.3 reports main descriptive statistics. The average return is similar for IPD, UNSM, BMN and BW_EW (around 3.0%), but is higher for GG (4.9%) due to two big outliers in 1984 and 1985, and is equal to zero for BW_CW due to two subsequent significantly negative figures – below -20% – in 1986 and 1987. Contrary to what we would expect, but in line with previous literature – Gatzlaff and Geltner [1998] – we find that our indices convey little more volatility than the valuation-based index. However, we think this is due to our method of construction that classifies the indices we obtain valuation-based rather than transaction-based indices (i.e. we compare prices with valuation, and in doing so, we assume either the most recent valuation is a proxy of the sale price, or the initial purchase price is the estimate of the first valuation). BMN and BW_EW show standard deviations very similar to the IPD index (and around 10.0%), while UNSM and BW_CW report a slightly higher figure (respectively 16.0% and 13.8%). GG is the only index showing a very different volatility (36.0%) due to its outliers in the first period of the estimation. Consequently, the profile of return per unit

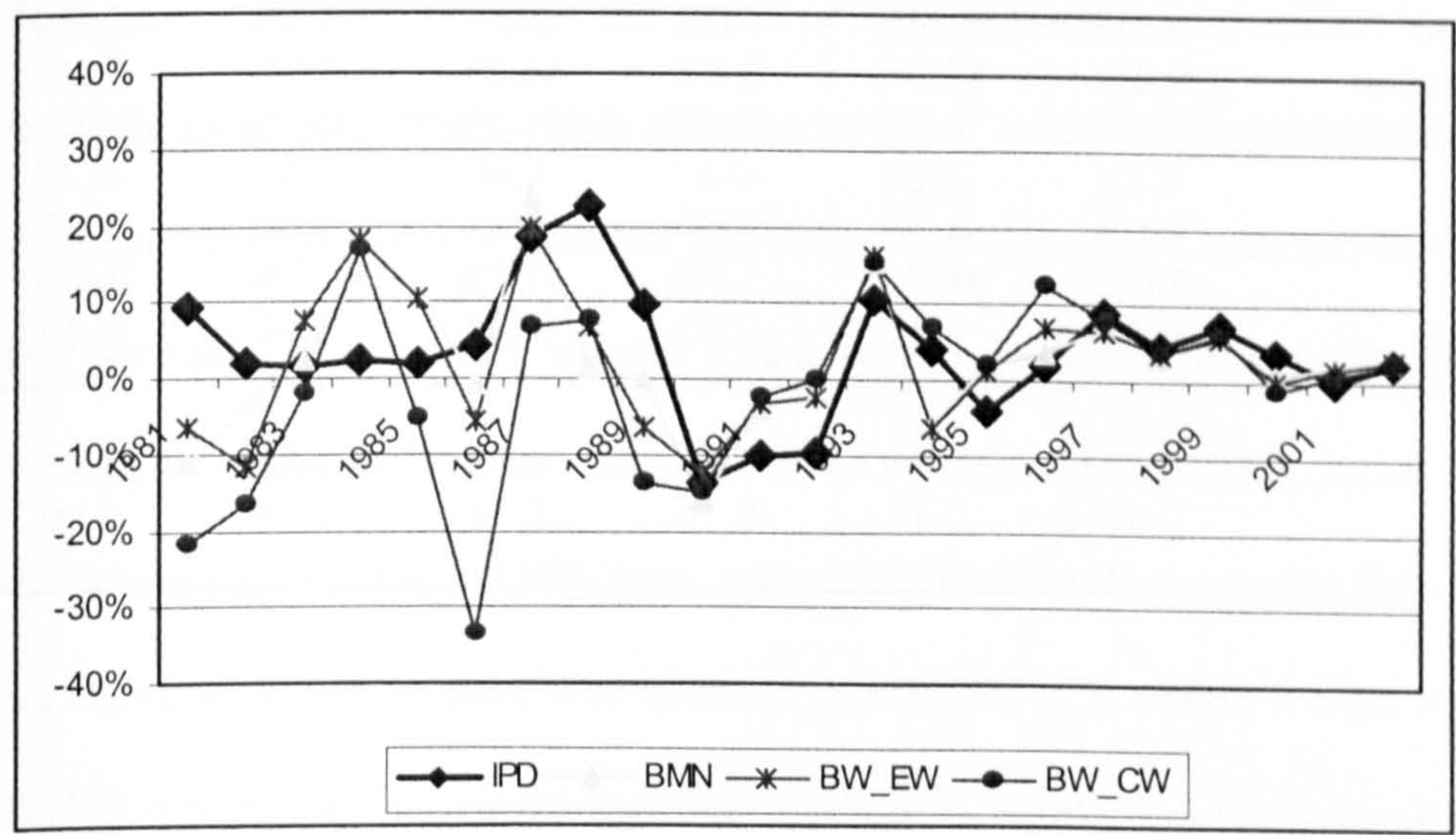
of risk is very similar for IPD, BMN and BW_EW (around 30.0%), while it is almost half of it for UNSM and GG and null for BW_CW. Furthermore, skewness and kurtosis suggest normality only in one case (BMN), with a positive thick tale for GG and a negative one for BW_CW.

Moreover, we think the autocorrelation parameter of order one represents a significant finding. If smoothing has been always an issue for the IPD index (0.44 autocorrelation), we obtain lower first-order serial correlations for all RMR indices (ranging between 0.00 and 0.23). Particularly we find that a simple equally-weighted index conveys less autocorrelation than a capital-weighted one, with a 0.13 difference attributable to the weighting system. We will return to this result with an insightful explanation later on, when we discuss results obtained with a restricted sample period (1987 - 2002).

Finally, we believe that the availability of a very thin sample during the first six years (i.e. from 1981 to 1986 the maximum number of observations for each year is 43) may have induced a bias in our findings. In fact, if we exclude the GG index from our plot (i.e. graph 5.3, panel A), we still obtain other RMR indices diverging from the IPD index, which, instead, is very stable in the early 1980s. This result represents the reason why we decide to base our overall finding on a shorter period, starting from purchases in 1987 onwards. Moreover, panel B reinforces our argument, by plotting the same RMR indices against an unsmoothed version of the IPD index. Even if performances show a more similar pattern with unsmoothed returns than with the IPD index, we still notice a significant divergence at the beginning of our sample period.

Graph 5.3: RMR return series excluding GG (sample: 1980-2002)

Panel A: Comparison with IPD index



Panel B: Comparison with Unsmoothed IPD index

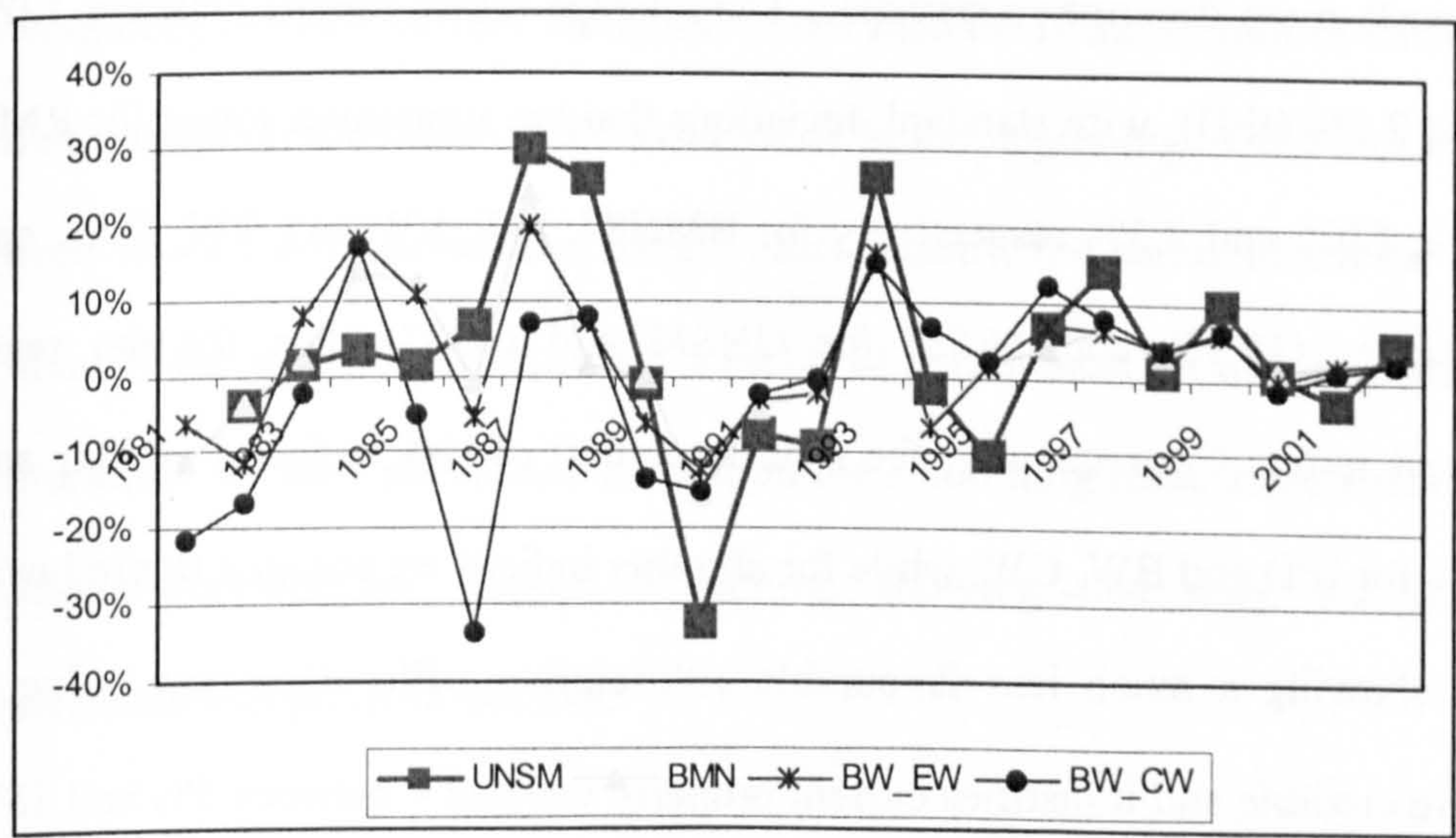


Table 5.4: Descriptive statistics (sample: 1987-2002)

	IPD	UNSM	BMN87	GG87	BW_EW	BW_CW
Average Return	2.5%	1.5%	1.0%	2.3%	1.4%	2.2%
Standard Deviation	9.3%	15.9%	6.8%	16.2%	7.0%	8.3%
Return per unit of risk	27.1%	9.5%	14.6%	14.0%	19.9%	26.6%
Skewness	0.10	-0.30	-0.51	0.80	0.01	-0.70
Kurtosis	3.02	3.70	4.60	2.74	3.08	3.13
Median	3.6%	0.0%	1.8%	-1.3%	1.7%	2.4%
Autocorrelation	0.49	0.02	0.02	-0.26	0.02	0.39
Jarque-Bera	0.10	0.21	1.18	1.52	0.06	1.04
Lilliefors	0.14	0.14	0.16	0.14	0.14	0.16

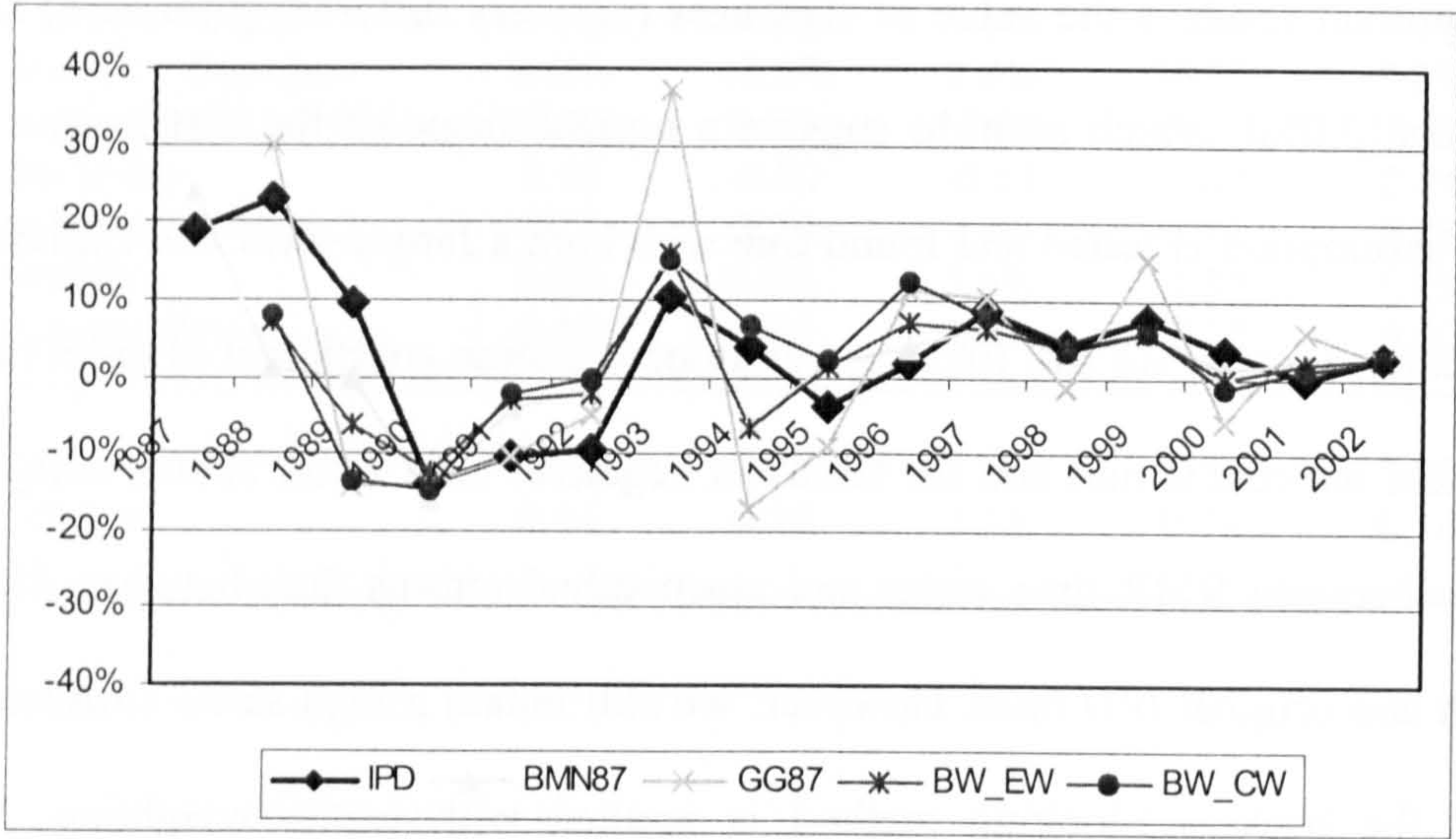
We then apply the four RMR methods to a shorter sample period starting from 1987. Table 5.4 reports main descriptive statistics. The average return ranges between 1.0% (BMN87) and 2.5% (IPD), with standard deviations that are sometimes lower for RMR returns (6.8%, 7.0% and 8.3% respectively for BMN87, BW_EW and BW_CW), and sometimes higher (15.9% and 16.2% for UNSM and GG87) than for the main valuation-based index. Consequently, the return per unit of risk is found similar and around 27.0% for IPD and BW_CW, while for all other indices we obtain a figure lower than 20.0%, showing a much less favourable risk/return profile. This new value is probably more credible and it justifies current property weights – between 5% and 15% – in multi-asset portfolios owned by institutional investors (i.e. a 27.0% figure

computed from valuation-based indices, in fact, would imply a much higher property weight).

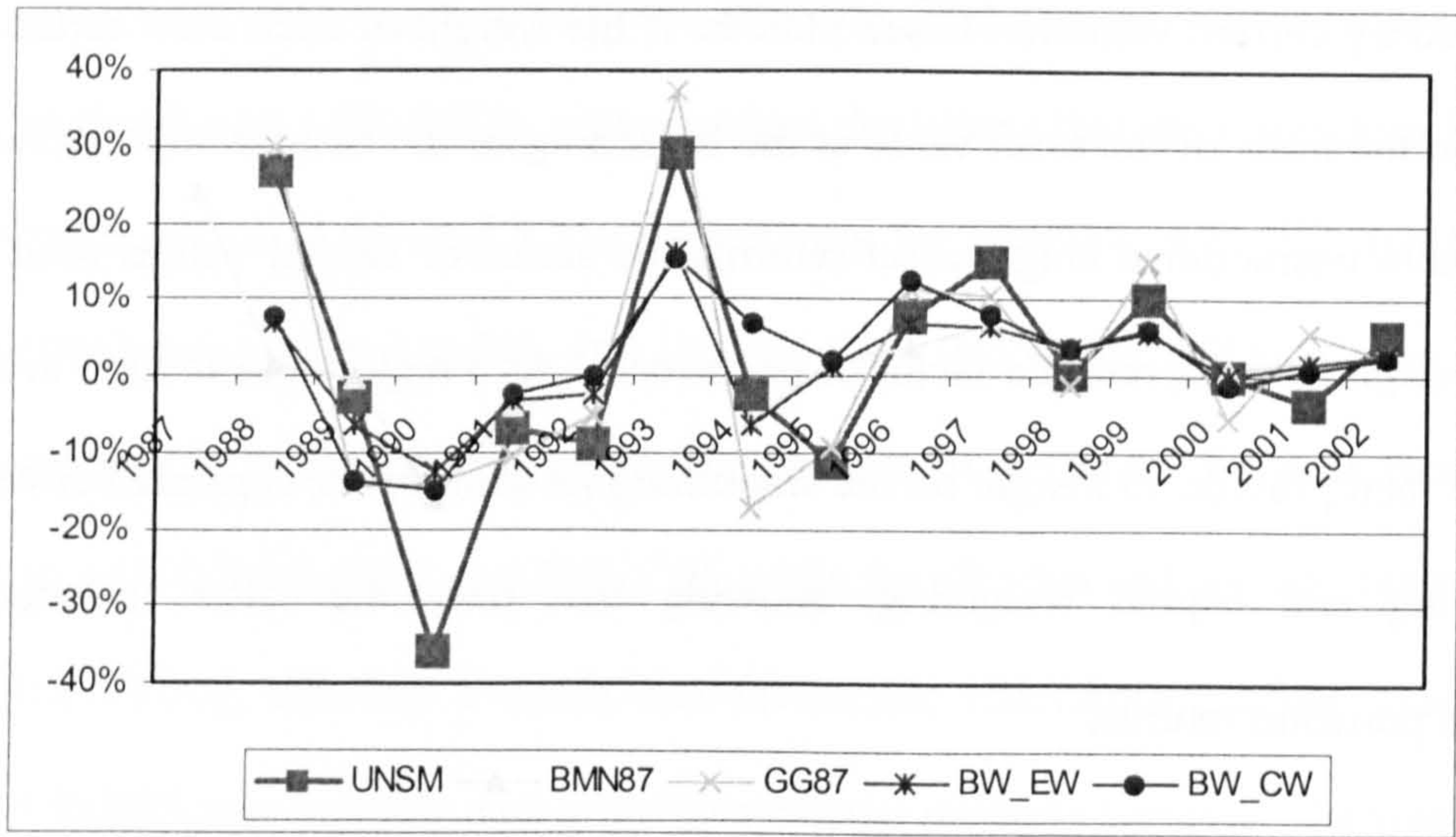
A second important result is the value of skewness (not very different from zero) and kurtosis (around 3.0%), which seem to suggest a normal shape of the distribution of returns. This assumption is tested and found true with both a Jarque-Bera and Lilliefors test for normality. Finally, we still find a lower autocorrelation coefficient of order one, which, for most indices, is null and for GG87 is negative. This result shows a higher comparability between RMR time series and unsmoothed returns than between RMR performances and original IPD ones. However, we still obtain a high serial correlation (0.39) when the backward-looking method is applied with capital-weighting. We attribute this finding to the fact that index smoothing may be due to the type of weighting used by current valuation-based indices. If the weight of each asset return is determined on the basis of the asset value at the beginning of the measurement period, even if we have unsmoothed single asset returns, the series of capital values used to identify the weight may represent a factor of persistence. As a major contribution to the literature, we then provide an insight on the smoothing issue since we separate between equal-weighting and capital weighting, showing that only the latter introduces persistence in portfolio returns.

Graph 5.4: RMR return series excluding GG (sample: 1987-2002)

Panel A: Comparison with IPD index



Panel B: Comparison with Unsmoothed IPD index



Furthermore, graph 5.4 seems to suggest that RMR returns lead the IPD index only in its original form (and not if it is unsmoothed). If the two panels are compared, there is clearly a more significant ‘anticipation’ of RMR performances on original valuation-based indices (panel A) than on unsmoothed indices (panel B). Particularly, panel B shows the capability of RMR measures to obtain plausible estimates of returns for direct investment in real estate, supposing the true estimate of these returns corresponds to an unsmoothed version of normally accepted valuation-based indices.

If our interpretation of the two previous graphs is correct, dependency measures should confirm it. Table 5.5 reports three matrices for each dependency measure. All RMR indices show a higher dependency with UNSM than IPD. Particularly, correlation coefficients increase by at least 35%, passing from a range included between 0.49 and 0.64 to a range included between 0.78 and 0.87. Kendall’s Tau figures are all above 0.60 when the term of comparison is the unsmoothed index and they are all below 0.50 if compared with IPD returns. Finally, Spearman’s Rho coefficients show an even higher increase, by passing from a range of 0.48-0.58 to a range of 0.75-0.85.

Following these results, we conclude that RMR indices reflect more unsmoothed returns than valuation-based indices. Thus, if we assume unsmoothed returns to be a proxy for transaction price movements, we may also consider RMR indices as performance measurements reflecting transaction-based rather than valuation-based information.

Table 5.5: Dependency matrices (sample 1987-2002)

Panel A: Pearson's correlation coefficient

	IPD	UNSM	BMN87	GG87	BW_EW	BW_CW
IPD	1***					
UNSM	0.85***	1***				
BMN87	0.59**	0.84***	1***			
GG87	0.64***	0.84***	0.74***	1***		
BW_EW	0.6**	0.87***	0.93***	0.9***	1***	
BW_CW	0.49*	0.78***	0.73***	0.72***	0.85***	1***

Panel B: Kendall's Tau

	IPD	UNSM	BMN87	GG87	BW_EW	BW_CW
IPD	1***					
UNSM	0.64***	1***				
BMN87	0.45**	0.62***	1***			
GG87	0.39**	0.64***	0.64***	1***		
BW_EW	0.5***	0.68***	0.79***	0.81***	1***	
BW_CW	0.49**	0.62***	0.62***	0.6***	0.75***	1***

Panel C: Spearman's Rho

	IPD	UNSM	BMN87	GG87	BW_EW	BW_CW
IPD	1***					
UNSM	0.82***	1***				
BMN87	0.52*	0.75***	1***			
GG87	0.48*	0.79***	0.82***	1***		
BW_EW	0.58**	0.85***	0.88***	0.95***	1***	
BW_CW	0.58**	0.82***	0.73***	0.72***	0.82***	1***

Finally, we expect this feature to cause a lead/lag structure between RMR returns and the IPD index, which should fade away when the IPD index is unsmoothed. In fact, when we “correlate” RMR return series with valuation-based performances (table 5.6, panel A), we obtain positive both contemporaneous and one-year-lagged dependency measures that are statistically significant. Moreover, in most cases, the one-year-lagged figure is higher and more statistically significant than the contemporaneous one.

However, when we unsmoothed the IPD series we obtain contemporaneous dependencies that are highly significant (all at 99% confidence level). One-year-lagged measures are only significant in few cases and, at the same time, show both a smaller value and a lower level of significance than contemporaneous dependencies (not more than 90% confidence level and only for a Spearman’s Rho coefficient).

We also run granger causality tests, but both the small number of observations and the annual frequency make the test not conclusive.

Table 5.6: Inter-temporal dependency measures (sample 1987-2002)

Panel A: Computation with IPD index

	Pearson			Kendall			Spearman		
	BMN87	GG87	BW_EW	BW_CW	BMN87	GG87	BW_EW	BW_CW	BMN87
Lag -2	-0.47	-0.31	-0.40	-0.64**	-0.28	-0.21	-0.28	-0.44**	-0.32
Lag -1	-0.29	-0.45	-0.45	-0.5*	-0.25	-0.38*	-0.34	-0.19	-0.31
Lag 0	0.59**	0.64***	0.6**	0.49*	0.45**	0.39**	0.5***	0.49**	0.52*
Lag +1	0.54**	0.62**	0.69***	0.74***	0.38*	0.56***	0.6***	0.47**	0.52*
Lag +2	0.16	-0.26	0.09	0.28	0.05	-0.10	-0.03	-0.03	0.10

Panel B: Computation with Unsmoothed IPD index

	Pearson			Kendall			Spearman		
	BMN87	GG87	BW_EW	BW_CW	BMN87	GG87	BW_EW	BW_CW	BMN87
Lag -2	-0.21	-0.14	-0.16	-0.35	-0.08	-0.05	-0.08	-0.23	-0.10
Lag -1	-0.06	-0.28	-0.23	-0.14	-0.08	-0.25	-0.16	-0.01	-0.10
Lag 0	0.84***	0.84***	0.87***	0.78***	0.62***	0.64***	0.68***	0.62***	0.75***
Lag +1	0.18	0.23	0.33	0.45	0.34	0.30	0.30	0.25	0.5*
Lag +2	-0.11	-0.56**	-0.25	-0.09	-0.08	-0.33	-0.15	-0.05	-0.10

5.5 CONCLUSIONS

We have constructed four different indices using initial purchase prices, capital expenditures/receipts and most recent valuations from a database of more than 7,000 properties. All four indices show a behaviour which is more similar to unsmoothed than to original valuation-based indices.

Since the size of our sample decreases the longer the period we use, we suggest using a simple method, which does not use all available information, but at least it does not imply dependence of more recent performances on earlier ones in the estimation process. We find regression techniques suggested in the literature are highly dependent on the size of the first year sample, with the presence of significant outliers in the residuals mainly for properties bought during the first period of the analysis. Specifically, when the GG method is used, we find heteroskedasticity in the residuals and use a robust Newey-West estimation, but this feature still remains to be solved more adequately.

For this reason we suggest to use a backward looking method (BW) that only uses the last updated information to compute returns. Particularly, we prefer equal-weighting to capital-weighting since the latter introduces smoothing, which is not found with the former.

The resulting BW_EW index shows an average return of 2.9% (vs. 3.3% for IPD and 3.0% for UNSM) and a volatility of 10.6%, only slightly higher than the one shown by a valuation-based index (10.0%), but lower than the unsmoothed one (16.0%).

Consequently, the return per unit of risk of our index (27.0%) lies between the one found with IPD performances (32.8%) and unsmoothed returns (19.0%). Moreover the BW_EW index conveys very little autocorrelation (0.10 first order coefficient) and tends to lead the IPD index and to be highly correlated with unsmoothed returns (0.87). Finally, we conclude that the “equally-weighted backward looking index” represents a good proxy for past returns of direct investments in real estate. This methodology can be used in markets with thin information since it employs much less data-points than a normal valuation-based index⁵¹. Moreover, the BW method is also suitable if the market does not show periodic property valuations since it uses only purchase prices and most recent valuations, which are easily available from primary sources such as insurance companies and pension funds (i.e. they normally keep a record of purchase price and date for each bought property still held in their portfolio). However, the number of properties included in the dataset is very important as the empirical analysis in the UK market has suggested. We have seen that when the sample of properties dropped from more than 100 to less than 50 in 1986, the estimation of returns was problematic. For this reason the applicability of this methodology to markets with thin information is dependent upon the availability of information for a minimum number of properties purchased in each year⁵².

⁵¹ If we consider, for example, a property bought in 1990 and showing no capital expenditures throughout the sample period (ending in 2002), a RMR index uses 2 data-points (initial purchase price and most recent valuation), while a valuation-based index needs 13 periodic observations (i.e. annual valuations) for that property.

⁵² A more detailed discussion of the applicability of this methodology in markets with thin information is contained in section 6.2.2.

Chapter 6

CONCLUSIONS AND FURTHER RESEARCH

In the introductory chapter we presented the main factors which limit the application of standard index construction methodologies based on transaction prices to real estate markets. We then used the second chapter to discuss four main methodologies used to create property indices and their main issues. Specifically, real estate markets adopt valuation-based indices as the standard measure of performance for several purposes: research, portfolio analysis and management, forecasting, etc. However, the construction of this type of indices requires the use of a significant amount of data (see section 2.2.3), which represents a real obstacle to the construction of historical property performances. While this obstacle is present in any market, newly established markets or markets suffering of a lack of transparency (i.e. markets with thin information)⁵³ tend to be most affected.

In chapters 3, 4 and 5 we developed three different index construction methodologies which use little information to create historical indices from either vehicle-based performances or individual property data. In order to assess the ability of these methodologies to represent “true market performances”, we applied them to the UK market, where a valuation-based index (i.e. IPD index) measuring private real estate returns already exists and can be used as a direct term of comparison. Finally, we acknowledged that valuation-based indices normally show a high level of persistence in returns (see section 2.2.2), which tends to grow as their frequency increases. Therefore, we also applied several unsmoothing procedures to test for the impact of smoothing on the relationship between our three indices and “true market returns”.

⁵³ Sometimes they are only available on hard copy.

A key issue in the construction of real estate indices in markets with thin information is the identification of existing data sources which are able to provide enough information. Specifically, we identified two main data sources to create a proxy for direct real estate returns:

- performances and characteristics of vehicles investing in direct real estate (which we properly adjust to account for gearing with a WACC model – see chapter 3 – and for gearing and a differential in liquidity from other stocks with a CAPM framework – see chapter 4);
- a limited amount of individual property data (which we use in place of the full set of information required by valuation-based indices – see chapter 5).

This concluding chapter is structured as follows: section 6.1 contains a summary of main results through an analysis of the return/risk profile and cyclical behaviour of the three newly created indices in comparison with original and unsmoothed IPD returns; section 6.2.1 discusses the main issues arising from the application of our index construction methodologies to markets with thin information; finally, in section 6.2.2 we suggest some areas of further research.

6.1 A COMPARISON BETWEEN METHODOLOGIES

6.1.1 Adjustments to vehicle-based indices

In chapter 3 and 4 we adjust returns of UK property companies. We adopt either a Weighted Average Cost of Capital framework (i.e. WACC) or a Capital Asset Pricing Model net of illiquidity costs (i.e. NCAPM) and obtain time series of de-gearred returns of property vehicles as a proxy for private real estate returns. Specifically, the WACC model – already applied in the literature – is updated with new market value information and for the first time applied to a monthly frequency, while the NCAPM method employs returns net of illiquidity costs to adjust for differences in liquidity between different sectors of the equity market.

In both models we also use a leverage ratio reflecting market rather than book values and computed from primary sources. Finally, we unsmooth direct property returns and analyse how adjustments made to both securitised and unsecuritised real estate returns affect the comparability between these two markets.

We find both WACC and NCAPM results are dependent on the frequency of the performance measurement.

For annual data, the adjustment made to both direct and indirect property returns improves the similarity of the risk/return profile of the two markets (see tables 3.4 and

4.4). On one hand, average returns do not change significantly for both securitised – they are slightly smaller with NCAPM than with WACC – and unsecuritised markets because the impact of the adjustment is normally reflected in the risk factor. On the other hand, adjustments to direct and indirect property performances respectively increase and reduce their volatility (with NCAPM showing slightly smaller figures than WACC), improving their similarity. Furthermore, both de-gearing and unsmoothing increase the dependency between private and public real estate markets (see tables 3.5, 3.6, 3.7 and 4.5). Unsmoothing is the major driving factor of the increase while de-gearing only plays a minor role (i.e. the increase in dependency obtained with unsmoothing is three times bigger than the one obtained with adjustments to securitised returns).

For monthly data, changes in volatility after the adjustment made to valuation-based indices tend to be more significant than for annual data (due to a higher smoothing effect). Moreover, the risk/return profile of direct and indirect real estate returns after the adjustments becomes similar only if we use a NCAPM framework – i.e. the WACC model does not improve the return per unit of risk, which ranges between 0.2 and 0.3 even after the adjustment (see tables 3.8 and 4.8). Finally, even if we adjust both securitised and unsecuritised returns, we do not obtain any improvement in the contemporaneous dependency between these two markets, which is never found to be significantly different from zero (see table 4.9). However, for some specifications of the NCAPM framework, the Spearman's Rho coefficient reaches a value of 0.15, while the WACC model leads to a maximum figure of 0.02.

When we analyse inter-temporal dependencies, instead, several coefficients are significantly different from zero for both models also with a monthly frequency. Specifically, the concordance between adjusted real estate vehicles returns and smoothed valuation-based indices (see table 4.10) shows positive coefficients (significantly different from zero) at four to seven month lags – the NCAPM also shows positive coefficients at lags one to three. With an annual frequency, however, the positive coefficient at lag one is smaller than the one at lag zero (see table 4.6). Therefore, if there is any price discovery, we expect the information diffusion process from one market to the other to be completed in less than one year. The granger causality test (see tables 4.7 and 4.12) confirms this hypothesis because statistical significance of securitised real estate “causing” unsecuritised real estate is only found when a monthly frequency is used (WACC shows a weak statistical significance). Specifically, the direct property market incorporates information seven months after the indirect property market, suggesting the latter leads the former by approximately half a year.

On the other hand, when we examine the inter-temporal dependency between adjusted indirect property returns and unsmoothed valuation-based indices (see table 4.11), coefficients using a monthly frequency become significant only at lags one, four and seven with a NCAPM framework using a gearing ratio computed with market values and our proxy for illiquidity costs measuring the “sensitivity of prices to properties turnover” (the WACC model and other CAPM specifications lead to positive figures at both positive and negative lags). Moreover, causality from securitised to unsecuritised

markets fades away, suggesting two plausible explanations. Either information is incorporated in indirect real estate markets and transaction-based indices contemporaneously (and successively transmitted into valuation-based indices), or real estate shares are priced according to the valuation of underlying assets (i.e. property portfolios), which tend to reflect a smoothing effect.

Finally, we find an optimum unsmoothing parameter, which maximizes the dependency between unsmoothed valuation-based indices and indirect property returns with an annual frequency (see graphs 3.9, 3.10, 3.11 and 3.12). This parameter is not dependent on the unsmoothing procedure, is in line with figures that are normally used in the literature (e.g. 0.40 to 0.55 for a first order autoregressive filter – see section 2.2.2) and justifies the current asset allocation to property of institutional investors (see Marcato and Key [2005]). This result could also be interpreted as an indication for the implied volatility of private real estate markets, which then would range between 12% and 16% per annum (as opposed to a 9.7% historical volatility obtained for annual valuation-based indices).

Overall, the empirical analysis on adjusted indirect property indices suggests that de-gearred securitised returns have useful information content and could represent a good proxy to describe long-run performances in private real estate markets. When valuation-based indices are unsmoothed, measures of dependency between these indices and adjusted indirect performances strengthen significantly. Assuming that unsmoothed direct real estate returns better reflect underlying transaction prices than original

valuation-based indices, this result suggests that property company data could represent a complementary source of information to current direct market series in both developed and newly established markets. When we use an annual frequency, we do not have any preference between a NCAPM or WACC model. On theoretical grounds, a NCAPM framework has the advantage to deal with leverage and differences in liquidity between equity sectors contemporaneously. However, empirically there is an advantage in using a WACC model because the NCAPM methodology cannot be applied in its original form due to the availability of only a small number of annual observations. The beta cannot be estimated on a rolling basis and we thus have to keep it constant throughout the period, obtaining a biased estimate of returns for earlier observations (see section 4.5.2 and discussion of graph 4.2 in section 4.6.1).

If we consider a monthly frequency, the use of property company data may give an indication of the behaviour of real estate market cycles. However, the conclusion is a weaker one, suggesting that there is information content in the data and that vehicle-based indices are helpful in understanding movements in transaction prices in the direct market. The adjusted vehicle-based index represents a complementary source of useful information in order to understand short-term movements in the direct market. When monthly data are used, we tend to prefer a CAPM framework since we find improvements in the risk/return profile (which does not change if we use a WACC method), positive contemporaneous dependency measures (even if they are not statistically significant) and a clearly defined lead/lag structure, which proves the existence of price discovery from securitised to unsecuritised markets with a seven

month delay. Finally, starting from a specific assumption about the relationship between illiquidity costs in equity and debt markets (see proposition 2 in chapter 4), we also find that this model theoretically implies (and empirically obtains) a lower return volatility after vehicle-based indices have been adjusted.

6.1.2 Repeated-measures regression indices

In chapter 5 we create four annual indices using individual property data: initial purchase price, capital expenditures/receipts and most recent valuation. All four indices show a behaviour which is more similar to unsmoothed than to original valuation-based returns (see graph 5.4).

Regression techniques are highly dependent on the sample size of the first period, where all significant outliers in the residuals are found. Specifically, the Geltner and Goetzmann (GG) method – see section 5.2.2 – requires a robust estimation since we find heteroskedasticity in the residuals. The Bailey, Muth and Nourse (BMN) method, instead, represents an interesting alternative as it yields similar results without using any information about capital expenditures/receipts (see section 5.2.1). It can therefore be used for markets with thin information where such data are not available.

Since all regressions show an estimation problem in the first period (as if they were suggesting the existence of a “data learning process”), we tend to prefer a backward looking (BW) method that uses only the last updated information to compute returns, starting from the last period of the sample. This method, at least, allows most recent

returns not to be affected by the estimation of past figures (see section 5.2.3). Particularly, we prefer equal-weighting to capital-weighting since the latter introduces smoothing, which is not found with the former (see table 5.4).

In line with the previous literature, when the BW index is compared with original and unsmoothed valuation-based indices, it shows similar average returns but it does not suggest a volatility of real estate markets being higher than the historical one from valuation-based indices. The return per unit of risk lies between original and unsmoothed valuation-based returns. Moreover, the BW index conveys very little serial correlation and tends to lead the IPD index and to be highly correlated with unsmoothed returns (see table 5.5). The contemporaneous dependency (almost equal to 0.9) is even higher than the one obtained with adjusted vehicle-based indices and this method should then be regarded as a very good proxy for unsmoothed private real estate returns. Finally, inter-temporal dependencies with IPD returns at lag one are all relevant and significantly different from zero (see table 5.6). However, coefficients are reduced when IPD returns are unsmoothed and positive figures at lag one that are significantly different from zero are only found when dependency is measured with a Spearman's Rho.

6.1.3 Adjusted vehicle-based returns or RMR techniques?

One may argue that there exists an *apriori* to prefer index construction methodologies based on individual property data rather than property company share prices. These

techniques are in fact more similar to standard methods currently adopted in real estate markets. However, the amount of data needed to produce repeated-measures regression indices is considerably greater than the set of information needed to adjust a vehicle-based index. Even if no periodic valuations are required to estimate RMR measures, the minimum number of properties that are necessary to compute a statistically significant return series may constrain the application of such methods in markets with thin information.

Since results using annual returns are similar for all methods (WACC, NCAPM and RMR), we conclude that the choice between the three approaches to construct a proxy for direct property returns should be driven by data availability (e.g. existence of a market of property company shares, availability of purchase prices of individual properties in company records). However, if the frequency is monthly, the consideration about data availability, together with the time consuming nature of the data collection process, suggest that adjustments made to unsecuritised real estate returns (with a NCAPM framework) are to be preferred to repeated-measures regression methodologies.

So far we have always investigated these methodologies in the UK context, which represents a market with good information flows. However, our conclusions require a final discussion to identify the major issues arising from an application of the three methodologies to markets with thin information.

6.2 APPLICATION TO MARKETS WITH THIN INFORMATION

6.2.1 Adjustments to vehicle-based indices

Both WACC and NCAPM methodologies need an elementary set of information: a share price index of real estate vehicles (e.g. property companies, real estate investment trusts) and its average gearing ratio. The composition and use of such data need to be analysed and some of the issues are common to both newly established markets with low information flows (e.g. Italy, Spain, Portugal, etc.), and more developed markets (e.g. UK, USA, France, Germany).

First of all, the existence of share price indices requires property vehicles to be publicly traded in the stock exchange. Thus, if the property market developed through the establishment of private vehicles, this type of information may be missing. Normally, however, some publicly traded entities exist and are used to construct indirect property returns in several markets. In Italy, for example, 12 vehicles – with a total capitalization of 4.7 billion Euros at the end of 2004 – compose the real estate sector of the COMIT index, which is the index produced by the Italian Stock Exchange.

The main issue arising in markets with thin information is the reliability of data composing the index. Firstly, property companies may have been established only recently. Thus the number of constituents may be low in earlier years and the index may

not be representative of the overall market (see FTSE guiding principles⁵⁴). If that is the case, one then may critique the choice of using a small number of property companies (corresponding to a small portion of the underlying direct property market) to obtain a proxy for private real estate returns. Secondly, this problem is sometimes magnified because index providers decide to exclude some companies from their sample. If we consider the European Public Real Estate Association (i.e. EPRA), for example, only one vehicle (i.e. Beni Stabili) composed the Italian index until 2002, regardless the fact that other indices (e.g. COMIT) included several other companies. Furthermore, the lack of an adequate number of constituents may represent a bigger problem the longer the historical sample period is. Thirdly, a difference in the portfolio composition between direct property markets and underlying assets held by real estate vehicles may create a bias in the performance measurement. Particularly in new markets, but also in well established markets, the portion of developments (as opposed to standing investments) composing the overall property portfolio is normally higher in vehicles than in private real estate indices – e.g. UK property companies show a slightly higher weight of developments than the IPD index. Furthermore, the composition of indirect portfolios may show over/underweighting in some sectors/segments (e.g. UK property companies tend to overweight Central London Offices). However, this problem is less significant than the previous one because return differences between sectors/segments are smaller than differences between standing investments and developments.

⁵⁴ “Ground rules for the management of the FTSE all-world index” (2002).

In markets where we have a valuation-based index, a fairer comparison between adjusted securitised and unsecuritised returns may be obtained by re-computing the valuation-based index according to the weighting of property vehicles because returns of standing investments, developments and several sectors/segments are known. However, if we start from indirect property returns, we cannot re-compute a proxy for private real estate returns according to its current portfolio composition.

The second type of data needed to adjust indirect indices is the gearing ratio. Some data providers (e.g. Datastream) already produce average gearing ratios at the index level. However, our empirical analysis showed the preference for ratios computed with market rather than book values. Information is then to be obtained from both secondary and primary sources. The market value of each company is given, at each point in time, by its share price multiplied by its number of shares and it is normally recorded by data providers such as Datastream, Bloomberg, or the Stock Exchange itself. On the other hand the value of outstanding debt and debt issues throughout the period may be obtained from primary sources (mainly balance sheets). The gearing ratio can then be computed using these two types of information, but the data collection from primary sources may be highly time-consuming⁵⁵.

A third major issue associated with the use of vehicle-based indices refers to the activity of mergers and acquisitions. These financial operations may induce a higher volatility which is not related to any property factor. This issue is even more significant in

⁵⁵ However, the amount of data required for the computation of the gearing ratio is still significantly smaller than the amount of data needed for index construction methodologies using individual property data.

markets with thin information because, if very few players possess highly sensitive information, the distortion in prices may be even bigger.

Finally, only for the CAPM framework, the computation of illiquidity costs requires the availability of transaction volumes. This information has normally been recorded in several markets only for the last few years. Therefore, for market with low information flows it may be even more difficult to retrieve a time series which is long enough.

6.2.2 Repeated-measures regression indices

Three different individual property data types are used in a repeated-measures regression: purchase price, periodic capital expenditures/receipts and most recent valuation.

The first piece of information can be easily obtained from primary sources. Accounting rules normally require (also in newly established markets) a record of the acquisition price of all company assets. However, since this item accounts for fiscal purposes, sometimes the recorded price may be different from the actual price of each individual property. Two examples may clarify this point. When there is the acquisition of an entire portfolio, some properties may be exchanged for a higher price because discounts are granted for other properties. This policy may allow the seller to minimise the impact of capital gain taxes, without changing the total price of the portfolio, which represents the main driving factor of the transaction for the buyer. A second example of price distortion is offered by intra-company transactions. The holding company may decide

either to reduce (e.g. when the buyer/seller shows a loss/profit) or to increase (e.g. when the buyer/seller shows a profit/loss) the price of all or part of the properties according to fiscal advantages rather than according to the dynamism of true transaction prices.

Furthermore, similarly to purchase prices, the availability of capital expenditures/receipts is normally guaranteed by accounting rules. This type of information is essential if we apply either a GG or a BW method. The only problem we envisage to collect these cash flows is the availability of such data at the individual property level rather than at the portfolio level. Capital expenditures/receipts may be recorded somewhere at the individual property level, but their availability for long time series is disputable. However, if we apply a BMN method, we do not need these data and we can still obtain results very similar to other methodologies that include them.

Finally, the third information for RMR techniques is the most recent valuation. During the last decade, investors strengthened their demand for improvements in the quality of public information. International accounting organisations therefore required companies to provide more up-to-date information at the most recent market value. This trend enables us, even in markets with thin information, to find vehicles which valued their properties recently and show individual property figures in company records (e.g. Italian insurance companies had, by law, the obligation to value their properties at least every five years and current International Accounting Standards require an annual valuation of real estate assets to the fair value). However, the existence of non simultaneous valuations may create some problems in the estimation process due to a small sample size at the end of the sample period. In order to explain this issue, we

present an extreme case. Let us suppose there is a market where valuations are made every three years, starting from the second one after the purchase (i.e. if a property is bought in year $[t-2]$, the first valuation will be at the end of year t). Hence, all properties showing a value at time t were bought at either time $[t-2]$, or $[t-5]$ – and valued for the second time –, or $t-8$ (and so on). If we use a backward looking method, we start from the computation of returns in year t with properties bought during that year and showing a value at the end of it. However, such properties do not exist because properties bought in year t will be valued for the first time in year $[t+2]$.

The issue of sample size is even more important for earlier years. In the UK analysis we already faced the problem of a thin sample during the early 1980s. In fact, the collection of past purchase prices is difficult because properties have to be held throughout the whole period by the same investor. On this regard fortunately, newly established markets tend to show a smaller turnover ratio than developed markets, and longer time series could then be estimated. Nevertheless, the restricted sample size at the beginning of the period does not preclude the construction of an index, but at the most, it shortens the obtainable time series.

Finally, RMR techniques reveal a main data issue, which is the significantly time consuming nature of the data collection, particularly if the information is on paper and not recorded electronically. However, once the data collection process is finished, they represent a reliable method to create a proxy for direct real estate returns.

6.3 FURTHER RESEARCH

So far we have identified three main methodologies to create a proxy for direct property returns when little information is available. These methodologies have been applied to the UK market and results compared with the current valuation-based index.

The first area of research we would like to pursue is the actual construction of real estate indices in markets with thin information. An interesting example is offered by the Italian market because we have already been able to collect a dataset of periodic valuations and cash flows of the property portfolio of a major insurance company. This set of information may be used to obtain a valuation-based index by applying the standard IPD methodology. The computed index would then represent the yardstick against which we could compare the three indices obtained using RMR techniques with individual property data, and a WACC or NCAPM framework to adjust vehicle-based returns.

A second area of research comes from the lack of valuation-based indices in markets with thin information. If a direct term of comparison is not available (as in the UK) or obtainable (as for Italy), we need to use other criteria and tools to determine the ability of newly created indices to represent a good proxy for private real estate returns. In this specific area, very little research has been done, and we intend to contribute to the literature by identifying other models of comparison – which may use financial and/or

economic variables, or the behaviour of other asset classes – to test for the ability of the three indices to represent real estate returns in markets with thin information.

A third area of research is the development of pure transaction-based indices. This need is not only felt in markets with thin information – where prices may be a useful source of available data alternatively to property company share prices or individual valuation-based data – but it also represents a major development required in most advanced markets. In the UK, in collaboration with IPD, we are already working on this project by applying several repeat-sales regression techniques to individual property data in order to measure the annual change in property prices. This new type of indices may be useful for market research (which needs more up-to-date information, avoiding the lagging effect of valuation-based indices) as well as for the construction of property derivatives, which are growing quite rapidly in the UK market even if, at the moment, only valuation-based indices (showing a very low volatility) exist.

Finally, unsmoothing helps us to understand how the underlying transaction market is behaving. However, the impact and origin of smoothing in the relationship between securitised and unsecuritised property returns has not been fully understood yet. The main concern is still the relative importance of the two main origins of smoothing, i.e. whether individual property issues contribute more towards smoothing than index construction issues. We plan to investigate the process behind smoothing found at the individual property level and the transmission effect to the portfolio level. This research

should analyse the level of smoothing for data inputs (e.g. yield, market rent) used in a simulated valuation model and use montecarlo simulations of individual property returns to replicate the transmission effect at the index level.

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Footnotes

¹ The IPD database is biased towards institutional ownership.

² “Liquidity in Commercial Property Markets” (2004), by Bond et al.

³ Source: RICS Appraisal and Valuation Standards, Part 1, Chapter 3, PS3.2.

⁴ If we assume a hypothetical market rent of 100, the market values at the beginning and at the end of the period will be respectively equal to: $CV_t = \frac{100}{0.06} = 1,666.67$ and $CV_{t+1} = \frac{100}{0.061} = 1,639.34$. Therefore, the decrease in value will be equal to: $\Delta Value = \frac{1,666.67 - 1,639.34}{1,666.67} = -1.64\%$.

⁵ See FTSE “Ground rules for the management of the UK series of the FTSE actuaries share indices” [2003].

⁶ See FTSE “Ground rules for the management of the UK series of the FTSE actuaries share indices” [2003].

⁷ E.g. Lee [2001].

⁸ The “Scott time series” is computed by applying the IPD methodology to the data collected from the portfolio of an insurance company – see Scott [1996].

⁹ RICS Appraisal and Valuation Standards (Red Book), 2005.

¹⁰ FGW.

¹¹ Source: Investment Property Databank, 2005.

¹² In the early 1970s only data of properties owned by eight funds were available (Source: Investment Property Databank).

¹³ Source: Investment Property Databank, 2005.

¹⁴ Source: Investment Property Databank, 2005.

¹⁵ Source: Investment Property Databank, 2005.

¹⁶ Another version of the material in this section was published in Booth and Marcato [2004a].

¹⁷ Source: Investment Property Databank, 2005.

¹⁸ From now on, we will refer to the BMN model.

¹⁹ Source: Investment Property Databank, 2005.

²⁰ National Association of Real Estate Investment Trusts. It represents the association of US Real Estate Investment Trusts (i.e. REITs) and it provides indices measuring the performance of this type of vehicles.

²¹ See Section 2.2.2 for a discussion on valuation smoothing.

²² E.g. in our repeated measures regression model we suggest to use, for each individual property, the acquisition price and the most recent valuation, instead of two successive sale prices.

²³ The main body of this chapter was published in the *Journal of Property Investment and Finance* and was awarded the “Gerald Brown Prize” as the best paper presented in Real Estate Investment and Valuation at the 2002 European Real Estate Society conference – see Booth and Marcato [2004b].

²⁴ Additionally, we also acknowledge that the taxation systems of equity, debt and direct investment in real estate are different, but we assume them being equal in our model.

²⁵ E.g. According to a mean-variance portfolio theory, the return/risk profile of direct investment in real estate does not normally justify current property weights in institutional investors' portfolios. A much higher weight would be expected because of the low risk / high return profile valuation-based indices show.

²⁶ We use a first order autoregressive filter, see Geltner [1993b].

²⁷ The correct applicability of the WACC model in markets with thin information may be limited by some key issues, which will be discussed in the final chapter (see section 6.2.1).

²⁸ The turnover rate (unless inverted) would represent a measure of liquidity rather than illiquidity.

²⁹ Graphs do not show illiquidity costs, but *illiq* measures before they are normalised.

³⁰ Source: Inland Revenue. Monthly rates are assumed to be constant throughout the year and changing only at the beginning of the year when the government intervenes.

³¹ E.g. mean, median, standard deviation, kurtosis, skewness and autocorrelation function.

³² Additionally to the Jarque-Bera test, we compute the *Lilliefors statistic* – a modified version of the Kolmorov-Smirnov goodness-of-fit statistic. It is very intuitive and it tests for normality when the population parameters are unknown. After ranking data values from the smallest to the largest one (x_1, x_2, \dots, x_n), the average (μ) and variance (σ^2) of the unbiased sample estimators are used to standardize data values. If $\Phi(z)$ denotes the standard normal cumulative distribution function and the empirical distribution function (i.e. EDF) of the data for every z is computed as $F_n(z) = \frac{\text{number of } z_{(k)}'s \leq z}{n}$, the

Lilliefors test statistics – with a p-value computed from the Dallal-Wilkinson (1986) formula – represents the maximum vertical distance between $F_n(z)$ and $\Phi(z)$: $L = \max\{F_n(z) - \Phi(z), -\infty \leq z \leq \infty\}$.

³³ Pearson's correlation coefficient, Kendall's Tau and Spearman's Rho.

³⁴ Granger causality test.

³⁵ The amount per unit of risk is computed as the ratio between average return and standard deviation.

³⁶ This result is consistent with previous literature applying a WACC framework – e.g. Booth and Marcato [2004b].

³⁷ Little information is used.

³⁸ The similarity of risk/return profiles and the dependency between market returns and CAPM-adjusted returns improved.

³⁹ The first observation (i.e. initial acquisition price) refers to the beginning of the holding period and the second one (i.e. most recent valuation) to the end of the holding period.

⁴⁰ Expenses relating to the refurbishment or development of a property, which have a direct impact on the value of the property itself.

⁴¹ Receipts for changes in the owner's interest in the property (e.g. sale of a portion of the building).

⁴² The estimation of real estate returns can be compared to the computation of spot yield curves from bond prices.

⁴³ Geltner and Goetzmann use either the sum of net income and capital expenditures/receipts or only capital expenditures/receipts to compute respectively total returns and capital growth rates. Since we only have information about capital expenditures/receipts (and not about income) we restrict our analysis to capital appreciation rates.

⁴⁴ This method contrasts with the one used by current standard valuation based indices, which only use standing investments to compute market returns (i.e. they exclude properties transacted and developed during the period).

⁴⁵ Contrarily to the BW methodology, current standard valuation-based indices would use this information through periodic valuations.

⁴⁶ E.g. mean, median, standard deviation, kurtosis, skewness and autocorrelation function.

⁴⁷ Additionally to the Jarque-Bera test, we compute the *Lilliefors statistic* – a modified version of the Kolmorov-Smirnov goodness-of-fit statistic. It is very intuitive and it tests for normality when the population parameters are unknown. After ranking data values from the smallest to the largest one (x_1, x_2, \dots, x_n), the average (μ) and variance (σ^2) of the unbiased sample estimators are used to standardize data values. If $\Phi(z)$ denotes the standard normal cumulative distribution function and the empirical distribution function (i.e. EDF) of the data for every z is computed as $F_n(z) = \frac{\text{number of } z_i\text{'s } \leq z}{n}$, the

Lilliefors test statistics – with a p-value computed from the Dallal-Wilkinson (1986) formula – represents the maximum vertical distance between $F_n(z)$ and $\Phi(z)$: $L = \max\{F_n(z) - \Phi(z), -\infty \leq z \leq \infty\}$.

⁴⁸ Pearson's correlation coefficient, Kendall's Tau and Spearman's Rho.

⁴⁹ Granger causality test.

⁵⁰ "The median time to sale, at 190 days, is a more representative figure. That still represents six months to sell the typical property from the funds examined. The longest stage is the period from initiation to heads of terms (median 88 days)". Source: IPF Liquidity Study [2004].

⁵¹ If we consider, for example, a property bought in 1990 and showing no capital expenditures throughout the sample period (ending in 2002), a RMR index uses 2 data-points (initial purchase price and most recent valuation), while a valuation-based index needs 13 periodic observations (i.e. annual valuations) for that property.

⁵² A more detailed discussion of the applicability of this methodology in markets with thin information is contained in section 6.2.2.

⁵³ Sometimes they are only available on hard copy.

⁵⁴ "Ground rules for the management of the FTSE all-world index" (2002).

⁵⁵ However, the amount of data required for the computation of the gearing ratio is still significantly smaller than the amount of data needed for index construction methodologies using individual property data.

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